GHENT UNIVERSITY

FACULTY OF ECONOMICS AND BUSINESS ADMINISTRATION

Internationalisation and Firm Performance

Angelos Theodorakopoulos

2017

Supervisor:

Prof. Dr. Bruno Merlevede

A dissertation submitted at Ghent University, to the Faculty of Economics and Business Administration, in fulfilment of the requirements for the degree of Doctor in Economics

Examination Board

Prof. Dr. Patrick Van Kenhove	Ghent University, Dean-President
Prof. Dr. Glenn Rayp	Ghent University, Academic Secretary
Prof. Dr. Bruno Merlevede	Ghent University, Supervisor
Prof. Dr. Gerdie Everaert	Ghent University
Prof. Dr. Joep Konings	KU Leuven
Prof. Dr. Gianmarco Ottaviano	London School of Economics and Political Science
Prof. Dr. David A. Rivers	University of Western Ontario

ἓν οἶδα, ὅτι οὐδέν οἶδα

Σωκράτης (469-399 π.Χ),

Ἀπολογία Σωκράτους (Πλάτων)

I know one thing,

that I know nothing

Socrates (469-399 BCE),

Apology of Socrates (Plato)

To Science

Acknowledgments

It is the beginning of September 2013 and I have just arrived in Ghent to start this new experience called Ph.D. Four years later, I am crossing the finish line with no regrets about my choice to embark on this trajectory, but only nice memories. A big part of these memories are (groups of) people who have contributed to this journey in their own special way. In turn, I would like to take the time to thank each one of them.

First of all, I would like to thank all Belgian institutions involved in creating a graduate system that provides an excellent working environment with generous scholarships. Operating under this system has allowed me to build a strong international network through conferences, workshops, seminars and a research visit at the London School of Economics (LSE). I consider this doctoral system a very important starting point for my academic career path and therefore advise any student to treat it as a unique experience and not as a "nine to five" job.

Next, I would like to thank my dissertation supervisor, Bruno Merlevede, for giving me the opportunity to start a Ph.D. with him, and, most importantly, for sticking to our initial agreement. This agreement included allowing me full flexibility in exploring topics of my own interest and conducting independent research. I truly appreciate the honesty and informality of all of our discussions that span from economics to ...! Over time, we built a relationship based on trust and respect that allowed me to become very productive and enjoy this four-year journey. Bruno, at the end of the day, I consider you more as a dear friend than a supervisor. Thank you for all of your guidance and support. I believe that this relationship will continue to hold both at a personal and professional level, conditional on you staying as cool as you are.

It is impossible to forget about Glenn Rayp and Gerdie Everaert–the additional internal members of my committee. Glenn, thank you for being open to interesting discussions that provided food for thought, your helpful comments on my dissertation, your support during all of my application procedures, and your novel character. Gerdie, you are the personification of the word meticulous and motivated. I am impressed by your commitment and passion for your work. Thank you for always making the time to discuss my research and provide valuable feedback, both at a technical and intuitive level. Your students should feel lucky to have you around, even if you cause them some ‘mental pain’ every now and then!

Moreover, I would of course like to provide gratitude to the external members of my committee. First, I would like to thank Gianmarco Ottaviano for giving me the opportunity to spend a semester-long research visit at the Centre for Economic Performance (LSE), and also for taking the time to read my dissertation and provide me with helpful feedback. I truly appreciate it! Second, I would like to thank David Rivers for all of his insightful comments both at a quantitative and qualitative level. David, as a big proponent of your work, I feel privileged to have you in my committee. I hope that one day we can collaborate together on cool projects. Finally, I would like to thank Joep Konings for all of his effort in going through my dissertation, but most importantly for materializing his interest in my work with a post-doc offer in KU Leuven. Joep, this means a lot to me and I look forward to working with you on interesting research ideas.

Continuing, it is imperative to thank Martine and Eva for their great work in making the department function smoothly and for always having their door open and a big smile. In turn, I would like to thank Koen Schoors for his unconditional help during my application processes and his vibrant personality.

A special thank you to my colleagues and friends at UGent. You have set the standards so high that it would be very hard for me to find a working environment equally fun and joyful. Thank you for your open-hearted goodwill and for being awesome! From this group, I would like to say a special thank you to Ruben “The White.” Ruben, it has been a pleasure to share an office with you, to party, to travel to conferences and to try to figure out this “mess” called productivity. You have a bright future ahead and I am sure that we will soon manage to finalise all of our beer-driven, ground-breaking research ideas.

I am grateful to Stijnoς Ronssoς for introducing me to Clio DF; the minifootball team that never gives up. To all members of the team, I would like to say thank you for the welcoming atmosphere and the fun moments. Every game was special to me and was my fuel for a productive next day at work. Don’t forget that all the fans whisper “Cliooo.”

The same holds for all members of the minifootball team of the Faculty, Economini. I never thought it would be possible to consume so much beer, cheese and salami after a football game.

Thank you “senior” Klaas Mulier for helping me integrate into the Belgian culture despite my unwillingness to learn Dutch. My best wishes to you and your family, and I hope we can keep in touch in the years to come. Also, I cannot forget about Sotiris Blanas, my dear friend and best buddy in academic conferences. Thank you for all the laughter and philosophical discussions, both about economics and life. There are more to come.

A special thank you to Rebecca Freeman and Pandi Klaniari “the editor in chief” for their unconditional help and moral support during the last, but most crucial, one hundred meters of this race. I am looking forward to all of the new experiences that are about to come! Before I move to my family, I would like to thank my best friends, Bill, Nikos, Tasos and Trias for bringing quality to my life and helping me become a better person.

At this point, I would like to thank my parents and brother. Μητέρα, πατέρα και αδερφέ, δεν υπάρχουν λέξεις να περιγράψουν το πόσο τυχερός και ευτυχής νιώθω που σας έχω δίπλα μου. Χωρίς την αγάπη και στήριξη σας τίποτα δεν θα ήταν το ίδιο. Οι αξίες και οι αρχές που πήρα μέσα απο την οικογένεια με καθοδηγούν σε κάθε μου βήμα. Σας ευχαριστώ για όλα!

Angelos Theodorakopoulos
Ghent, 24 August 2017

Table of Contents

List of Figures

List of Tables

1 Introduction

1.1 General Background

The capacity of an economy to produce goods and services is the result of economic activity that occurs in a complex web of interdependent processes. In recent decades, decreases in trade and communication costs have resulted in increased interconnectedness among economies. This is also known as the wave of internationalisation, which is characterised by the emergence of production sharing across nations (Johnson and Noguera, 2012), foreign direct investment (Gestrin, 2016) and international mobility of human-capital (Freeman, 2010).

In a distilled framework, we can think of the economy as having three key players: consumers; producers; and institutions. Consumers increase their utility by demanding the available goods and services in the economy. Producers combine various inputs to make inputs for other production processes, or final output for consumption. In turn, institutions set the regulatory environment in which firms operate and guarantee law enforcement for all transactions in the economy.

Production units (henceforth firms) are considered the focal point of modern economic systems. While the role of consumers and institutions is indispensable, firms typically receive the most of attention in policy making circles: they are seen as main drivers of economic growth through production, job creation, trade and innovation. Therefore, understanding how firms function and make decisions is essential to welfare-enhancing policy-making. In an ideal world, we (researchers/policymakers) could identify a firm's underlying processes by fully specifying its entire production structure (alternatively production technology). However, in the real world, this is practically impossible because many inputs to these processes are either unobservable (e.g. management practices, acquired characteristics of workers, innovation, etc.) or hard to measure with scientific objectivity (e.g. innate characteristics of workers, know-how, etc.)

Given the limited 'access' to the full set of information, we can only identify the production technology of a firm up to a certain extent. The unidentifiable component to be recovered is treated by the literature as an unobserved 'residual' term, labelled "productivity." Intuitively, it captures the extent to which firms depend on certain processes and technologies that we cannot observe in the data. Frequently, productivity is treated as a 'black box,' however, I prefer to call it our 'extent of ignorance.'[1] This is because, similar to the observed part of production technology, productivity has an unobserved underlying structure with various determinants. Such determinants could be either actions of the firm (e.g. importing, exporting, offshoring, etc.) or changes in its operating environment (e.g. opening up to trade, external trade shocks/crises, changes in regulatory environment, etc.).

The level of complexity of this underlying structure considerably rises due to endogenous or exogenous changes induced by the latest wave of internationalisation. Indeed, there is a consensus in the theoretical trade literature that productivity heterogeneity at the firm-level is a key dimension for explaining various observed adjustments induced by the internationalisation of economies (Melitz and Redding, 2014). Therefore, productivity needs to be explored thoroughly at the micro-level in order to unravel its true determinants and hence its relative importance for economic growth. Because productivity is not a directly observable outcome, we are left to compute/estimate it to the best of our ability.

Several productivity indices have been proposed at the firm-level, ranging from single factor productivity to total factor productivity. The former is calculated as output per unit of input (e.g. labour productivity) and is mainly convenient for validating theoretical

[1] Abramovitz (1956) was the first to call it as "a measure of our ignorance."

predictions about productivity. However, labour productivity is as an incomplete measure of performance since it disregards the contribution of other equally important inputs (e.g. capital and material). As such, total factor productivity has gained popularity as the most representative proxy for productivity. In response, a series of estimation techniques has emerged in the applied production function estimation literature, with structural approaches prevailing (Van Biesebroeck, 2008).

Structural approaches include both dynamic panel methods (Arellano and Bond, 1991; Blundell and Bond, 1998, 2000) and proxy variable methods (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2016). The main focus has been to solve for endogeneity, also known as 'simultaneity' or 'transmission bias.' Such bias originates from the fact that firms know their productivity level when they decide which inputs to use (Marschak and Andrews, 1944). Overall, this leaves researchers to choose from a basket of estimators, each of which has its own limitations depending on the application of interest and quality of available information.

Despite their popularity and prevalence in applied work, proxy variable methods are based on a set of restrictive assumptions that could fail to hold in various economic environments. Such failure translates to potentially serious identification issues. However, a considerable amount of empirical work across various strands of the literature systematically disregards the sensitivity of these estimators. This could lead to biased productivity estimates and, in turn, false conclusions about its true determinants. If the case, inaccurate policy recommendations stemming from research would ensue.

1.2 Contribution

With this in mind, the major contribution of my dissertation is twofold. First, I underscore the importance of productivity measurement by demonstrating how different measures, assumptions and estimation procedures affect economic conclusions. For this, I focus on commonly ignored misspecifications when identifying both productivity and its determinants, relative to a 'state of the art' approach. I aim to raise awareness about the sensitivity of results to estimation methods and provide empirical support for the 'superiority' of a certain estimator. Note that this estimator is not a panacea; it is also based on assumptions that could potentially prove restrictive. Nevertheless, it is the best available alternative in terms of both the potential biases it corrects for and its empirical robustness.

Second, building on the proposed state of the art estimator, I try to fully explore the determinants of productivity. Since we live in an increasingly complex world, it is important to 'back out' the determinants of productivity rather than simply assume they are randomly generated. In an internationalised and interconnected context, the aspects that I explore include trade, supply chains of production, input market imperfections and ownership structures.

Overall, knowing which type of firms have significantly been driving the economy or suffering during good and bad times is expected to provide policymakers and institutions with a strong reference point for shaping future policies.

1.3 Methodological Approach

Throughout all chapters, I use a state of the art production function estimation procedure proposed by Gandhi, Navarro, and Rivers (2016) (herein GNR). I empirically argue that this is the most competitive available procedure to identify productivity, compared to other proxy variable estimators.

Despite their popularity and prevalence, proxy variable methods suffer from identification issues when the production function contains at least one flexible input such as materials. These issues are in no way new. They have been highlighted by Mendershausen (1938); Marschak and Andrews (1944); Bond and Söderbom (2005); Ackerberg et al. (2006) and more recently formalised by GNR. Intuitively, there is not enough variation outside the production function system to identify the flexible input.[2]

To circumvent this problem, applied economists have focused on value-added production functions where the flexible input, materials, is subtracted from output and thus 'disappears' from the production function. Such a specification, however, will fail to identify the true variable of interest, i.e. TFP, even under very strong assumptions

[2]Firm specific prices, to the extent that they are exogenous, can potentially serve as instruments for flexible inputs and be used to solve for the identification problem (Doraszelski and Jaumandreu, 2013). However, in practice it is hard to find prices at the firm/plant level that reflect differences in expected rather than chosen prices (Griliches and Mairesse, 1999; Ackerberg et al., 2007). Therefore, in most datasets, prices will capture market power and input/output quality differences rendering them endogenous (Fox and Smeets, 2011; Kugler and Verhoogen, 2012; Atalay, 2014).

(Bruno, 1978; Diewert, 1978; Basu and Fernald, 1997). Estimates suffer from a value-added bias causing the dispersion and heterogeneity in TFP to be overstated. Intuitively, one erroneously attributes the variation of material inputs to productivity and resultantly ends up with a distorted image of the productivity distribution, which can cause misleading policy implications.

GNR propose a simple estimator for gross-output production functions with at least one flexible input. They establish identification by exploiting information in the first order condition with respect to the flexible input from the firm's static profit maximisation problem. This flexible approach controls for both the transmission and value-added bias. It imposes no specific functional form, nor does it rely on strong assumptions used by alternative proxy variable frameworks, for instance the assumption of scalar unobservability to invert the proxy function (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2006). In line with most of the the proxy variable methods, the GNR procedure follows two-steps and allows us to both estimate the production function and identify the potential determinants of productivity. This is the baseline procedure upon which inference is drawn and empirical robustness towards alternative assumptions and procedures is tested throughout my dissertation.

1.4 Data

Given the empirical nature of the dissertation, access to firm level data was essential. In Chapter 2, I use the Annual Accounts, VAT declarations and Transactions Trade dataset from the National Bank of Belgium (NBB). The combined dataset is representative of the Belgian manufacturing sector with detailed information on the balance sheet and trade activities of individual firms. This is a rich dataset that eliminates potential biases towards large firms and is particularly suitable for providing broader insights into various firm characteristics and their relative importance for aggregate economic activity.

For the remaining chapters I draw upon information in the Augmented Amadeus (AUGAMA) and the European Multinational Network (EUMULNET) datasets. These datasets are constructed by Merlevede, de Zwaan, Lenaerts, and Purice (2015) using information from Amadeus, a European firm-level database collected by Bureau Van Dijk Electronic Publishing. Specifically, the AUGAMA and EUMULNET datasets provide a consistent time series that correct for the possibility of firms being dropped from annual observations due to having exited the market. The datasets provide detailed information at the balance sheet and ownership level for a panel of firms across 26 European countries for the period 1996-2014. Merlevede et al. (2015) describe the construction and representativeness of the data at length. The countries, sectors and periods considered in each of the last three chapters depend on the research question and representativeness of the data required to address it.

1.5 Empirical Applications

In light of the above, my Ph.D. contains four distinct chapters, which feed into the two main contributions that I bring to the intellectual community. In what follows, I explain each chapter in turn.

1.5.1 Aggregate Productivity and Trade

In Chapter 2, I, along with my co-author, examine the micro-level determinants of aggregate productivity growth for the Belgian manufacturing sector during the period 1998-2012. Given the lack of consensus on how to compute and decompose aggregate productivity we start this chapter by demonstrating the presence of biases in the decomposition of aggregate productivity. Such biases are induced by different productivity indices even within decomposition methods. We confirm important biases arising from ignoring output-price differences across firms, estimating physical productivity under varying assumptions (e.g. timing of demand shocks), assuming common production technology at the manufacturing instead of the industry level and sample selection. We show that failing to correct for these biases may result in false conclusions about the evolution of aggregate productivity and the decomposed components.

After controlling for such biases, we decompose aggregate productivity based on groups of economic significance. We introduce a new dimension to the decomposition based on firm-attributes. This allows to assess whether there is a handful of firms driving aggregate productivity. Results suggest that large incumbent firms that engage both in exporting and importing determine the evolution of aggregate productivity. Over time, the increase in their average productivity dominates the steady decrease in the covariance between their market shares and productivity. This pattern is more intense after the burst of the 2008 financial crisis. All other groups contribute negatively, with signs of convergence in some cases. Finally, we provide a multi-country extension of our analysis using the AUGAMA dataset containing manufacturing firms from 18-EU countries. In addition to the previous results, we see that the within-firm component of firms from advanced EU nations is driving aggregate productivity of the manufacturing sector in Europe.

Overall, firms increase their productivity over time. Furthermore, those that experience the largest increases are both more deeply engaged in internationalisation and larger in size. All other firms lag behind and prevent aggregate productivity from reaching its full potential.

1.5.2 Supply Chains

Chapter 3 analyses whether indirect effects of internationalisation occur through the domestic supply chain. A large literature has examined the relationship between export and import behaviour on the one hand, and direct productivity effects of firms'/industries' offshoring behaviour on the other. Yet, potential indirect or spillover productivity effects of internationalisation have received less attention. I, along with my co-author, analyse potential productivity effects for a given firm that are associated with the internationalisation behaviour of other firms in the domestic economy. Since sharing new knowledge with related parties along the supply chain is more likely than sharing it with competitors, we focus on the effects of internationalisation by local clients and suppliers of a given firm. Local firms may then experience indirect productivity effects of internationalisation through participation in the domestic supply chain.

We investigate productivity effects for a given firm resulting from the internationalisation behaviour (i.e. import or export of intermediate inputs) of domestic upstream and downstream industries. We consider a small open economy to analyse productivity effects along the supply chain driven by trade in intermediates in related industries. We combine firm level data for Belgian manufacturing firms for the period 1995-2011 with input-output tables. The latter are used to construct industry-level measures of inter-industry offshoring and inshoring intensities based on a measure proposed by Merlevede and Michel (2013).

As in most empirical international trade research, productivity measurement is a core element in our analysis. Therefore, we point to common specification biases in applied work before interpreting the overall effects with our most preferred methodology. Our results can be summarised as follows. First, we demonstrate and confirm important biases that arise from ignoring the dynamic nature of productivity and specifying a value-added rather than a gross-output production function. Failing to correct for these biases may thus result in false conclusions about productivity's true determinants.

Second, only upstream inshoring, i.e. the export of intermediates by a given firm's local suppliers, appears to be a robust channel of inter-industry productivity effects in Belgium. Sourcing from industries that also export these intermediates is associated with higher productivity levels of a given firm. This effect likely stems from access to intermediates of higher quality that are also exported. In support of our result we find these effects to be stronger for firms and industries that are less likely to be directly internationally involved. The effect is more prominent for smaller firms, for firms with non-multinational status, and for firms in relatively upstream and/or low-skill intensive industries. Finally, we do not find such effects if the destination of the exported intermediates is either China or Eastern Europe.

1.5.3 Market Imperfections

In Chapter 4, I examine how changes in the operating environment of firms coupled with increased international trade affect firm performance. More specifically, I estimate the firm-level effect of frictions in the input market on productivity across various types of firms. Even firms operating in economies with the most flexible input markets face adjustment costs that impact both firm-level and aggregate outcomes (Hamermesh and Pfann, 1996). Input market rigidities can be seen as a financial constraint that affects the firm's investment decisions and thus its productivity. This relationship is potentially amplified by the interaction with trade and trade frictions. However, neither theoretical nor empirical literature have introduced a consistent way of identifying the impact of all input market rigidities on firm-level performance.

I bridge this gap by estimating the impact of input market frictions on firm performance. Firm-level frictions in capital and labour are expressed as the wedge between the marginal revenue product and marginal cost of each input, respectively. I introduce them in a standard model of production function estimation to directly gauge their effect on future productivity as well as the production function's parameters. For this analysis, I use the AUGAMA dataset with firm-level information on the manufacturing sector of 16 EU countries for the period 2002-2007.

On the one hand, firms facing increased labour market frictions experience increases in their future productivity that are smaller for exporters. This suggests that domestic firms are less willing to incur the costs associated with adjusting their tangibles, i.e. workforce. Hence, they rely relatively more on intangibles, i.e. organisation and managerial practices, that increase their future productivity via learning mechanisms. On the other hand, productivity effects from capital market frictions are less prevalent and uniform for all types of firms, pointing to the fact that capital is less-flexible and more-costly to adjust.

1.5.4 Ownership Structures

Finally, Chapter 5 explores how ownership structures shape the production technology and productivity of firms. The literature documents a scarcity of firms transferring tangibles within ownership structures. This is suggestive of the theoretical argument that firm ownership is primarily used to facilitate the efficient transfer of intangibles. In this paper, my co-author and I analyse the validity of this alternative explanation.

Using both the AUGAMA and EUMULNET databases, we carefully construct a European panel of majority owned parent-affiliate relationships with full information on both sides. In turn, we extend the state of the art production function estimator, i.e. GNR, to account for transfers of intangibles between the parent and its affiliate, and effects on the future productivity of affiliates.

We find that the productivity of the parent is both a significant intangible input in the affiliate's production technology and a key determinant of the affiliate's productivity dynamics. Domestically owned affiliates experience larger technology transfers from their parents while foreign owned affiliates benefit more from productivity increases induced by learning mechanisms. Overall, we identify, at the firm level, the importance of productivity transfers from various types of ownership structures and confirm the theoretically based argument that firm boundaries exist to facilitate the transfer of intangibles.

2

Compositional Changes in Aggregate Productivity in an Era of Globalisation and Financial Crisis*

2.1 Introduction

Policymakers consider productivity a key element of economic growth. However, trends in aggregate productivity are uninformative about their micro-level determinants which shed light on productivity itself. As such, various alternative methods to decompose aggregate productivity have been proposed. The decomposition literature spans from the seminal contributions of Baily et al. (1992) and Olley and Pakes (1996) to the most recent contribution of Melitz and Polanec (2015). The ultimate goal is to capture essential microeconomic sources and assess their relevance to aggregate productivity.

*This chapter is based on a paper co-authored with Catherine Fuss who is affiliated with the Economics and Research Department of the National Bank of Belgium, Berlaimontlaan 14, 1000 Brussels, Belgium and Université Libre de Bruxelles, e-mail: `catherine.fuss@nbb.be`. We thank Ruben Dewitte, Gerdie Everaert, Rebecca Freeman, Joep Konings, Bruno Merlevede, Gianmarco Ottaviano, Glenn Rayp and David A. Rivers for their comments and suggestions. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the National Bank of Belgium or any other institution to which the authors are affiliated. All remaining errors are our own. The extension of the application in Section 2.4.3 is based on a paper co-authored with Bruno Merlevede.

Decomposition analyses typically include two basic steps. First, since productivity of the aggregate is not directly observed, researchers rely on measures of aggregate productivity. These measures are computed as weighted averages of firm-level based productivity indices, i.e. labour productivity or total factor productivity.[1] Second, the analysis proceeds with using one of the available methods to decompose aggregate productivity. However, there is no consensus in the literature on which approach to follow; the choice depends directly on the research question and micro-level data at hand.

The majority of the decomposition methodologies focus on shifts in the distribution of firm-level productivities (within-firm) and the reallocation of market shares (between-firm) for various groups of firms. These groups mainly include entering, exiting and incumbent firms. However, firms operate in a globalised environment where competitive forces lead to productivity-enhancing restructuring. It is has been shown, both empirically and theoretically, that the most productive firms select into internationalisation, i.e. trade and FDI (Bernard and Jensen, 1999; Melitz, 2003; Helpman et al., 2004), and learn once they engage in such activities (Kasahara and Rodrigue, 2008; De Loecker, 2013). Such firms have higher sales, pay higher wages, and are more capital and skill intensive. Most importantly, only a few of these firms account for the bulk of internationalised activity (Mayer and Ottaviano, 2008).

To better understand the microeconomic determinants of aggregate productivity, research on this topic should include decompositions that are based on firm attributes of economic significance, e.g. trade, size, skill intensity, geography, etc. To our knowledge, only a few studies on the decomposition of aggregate productivity take these factors into account. Böckerman and Maliranta (2007) test for regional differences in the aggregate productivity growth of the Finnish manufacturing sector.[2] Bartelsman et al. (2013) find that variation in distortions (i.e. overhead labour and quasi-fixed capital) can explain cross-country differences in the resource reallocation component. Collard-Wexler and De Loecker (2015) examine the reallocation of resources within and between different types of production technology in the US steel industry.

For the case of Belgium, Van Beveren and Vanormelingen (2014) find that human capital intensive and/or internationalised firms exert higher aggregate productivity growth

[1] This approach is also known as 'bottom-up' (Balk, 2016).

[2] Also for Finland, using a similar dataset, Hyytinen et al. (2016) exploit cross-regional differences to illustrate their proposed procedure for statistical inference using the Olley and Pakes (1996) decomposition.

which is driven by the within-firm component. However, they use a revenue-based productivity measure. Both theoretical (Melitz and Ottaviano, 2008; Edmond et al., 2015) and empirical (De Loecker et al., 2016; Garcia-Marin and Voigtländer, 2013) studies confirm that variable markups are an important margin of adjustment for firms during various trade and regional integration policies.[3] As such, revenue-based productivity measures are also driven by the variation of firm-specific prices (Foster et al., 2008; De Loecker, 2011). This is bound to bias both the contribution and evolution of the decomposed components, as noted by Petrin and Levinsohn (2012) and confirmed by Eslava et al. (2013) who find larger trade-induced effects on allocative efficiency for price-adjusted productivity measures. Therefore, markups/prices consist of an important margin.

Overall, two important observations emerge. On the one hand, the literature delivers a plethora of results that vary quantitatively and qualitatively, even within decomposition methods. Such discrepancies are potentially driven by biases in the estimates of micro-unit productivity indices, which are mechanically transmitted to aggregate productivity measures. On the other hand, the decomposed components mask potential heterogeneity induced by various attributes of the firm. In both cases, we can end up with a distorted image about the micro-foundations of aggregate productivity, how they evolve over time, and how they react to changes in the operating environment of firms.

In this paper, we examine both of the above cases. First, we assess the effect of biases on various productivity indices for a given decomposition method of aggregate productivity. Such biases are frequently ignored in the empirical literature when computing firm-level productivity and include: using single factor instead of total factor productivity; the estimation of revenue instead of physical productivity;[4] the estimation of physical productivity under alternative assumptions for the timing of the demand shocks; the presence of differences in production technology across industries; and the selection of samples with larger firms.

[3]In line with this argument, Epifani and Gancia (2011) show how the distribution of markups distorts the allocation of resources. Thus, trade can affect welfare through distributional changes in markups. Similarly, Peters (2013) considers the case where misallocation stems from output market imperfections.

[4]Foster et al. (2008) examine the effect on the components of aggregate productivity growth from using revenue based productivities. They use a dataset with information on output prices and quantities and thus directly observe measures of physical productivity. However, such datasets are rare and researchers mostly rely on monetary values and aggregate price deflators. As such, further structure and assumptions are required to estimate physical productivity.

Second, we proceed using the most competitive productivity estimates available, i.e. the case of imperfect competition in the output market where demand shocks are observed by the firms post production and the production technology varies across industries for a representative sample of firms. Note that the chosen estimator is not a panacea; it is also based on assumptions that could potentially prove restrictive. Nevertheless, it is the best available alternative in terms of both the potential biases for which it corrects and its empirical robustness. With these estimates in hand, we decompose aggregate productivity based on economically significant firm attributes, i.e. trade, size, geography, and combinations.

For the analysis, we use a detailed firm-level dataset representative of the Belgian manufacturing sector, for the period 1998-2012. The following findings emerge. Despite the empirical convenience in validating theoretical predictions about productivity, single factor productivity (e.g. labour productivity) leads to biased empirical conclusions about 'true' productivity (e.g. total factor productivity). Moreover, we confirm significant biases in the evolution of aggregate productivity in the absence of controls for output-price differences across firms (Foster et al., 2008).

Similar biases emerge when we estimate physical productivity (i.e. à la De Loecker, 2011), under seemingly similar modelling assumptions. For example, if demand shocks are observed by the firm when deciding its inputs, physical productivity cannot be separated from markups and demand shocks without additional information, i.e. physical output or firm level prices. On the contrary, by assuming that demand shocks hit the firm ex-post production we can back out a measure closer to true physical productivity that we also consider the most competitive one for our decomposition analyses. Equally important is the bias from estimating production functions at the manufacturing instead of the industry level. In this case, we erroneously attribute variation from cross-industry differences in production technologies to aggregate productivity. Finally, sample selection, i.e. sample with larger firms, induces non-negligible biases in decomposition results.

After controlling for the aforementioned biases, we find that the reallocation of resources across firms has been decreasing steadily since 1998, with a drop during the 2008 financial crisis. Van Beveren and Vanormelingen (2014), using the same database for the period 1997-2009, find the opposite effect, i.e. a positive contribution of the reallocation mechanism on aggregate productivity growth. However, we see that this discrepancy in results is driven by price differences in their revenue-based productivity estimates,[5] supporting our expectations about the significance of distributional changes in markups.

On the contrary, a decreasing trend in average firm productivity was reverted during the 2008 financial crisis. Note that the decreasing trend is mainly induced by small-sized firms which account for more than half of the sample size. Also, entering and exiting firms are minor contributors to aggregate productivity growth. This can be reconciled with the findings of Garcia-Macia et al. (2016) where incumbent firms that rely on own-product improvements instead of creative destruction appear to be the drivers of aggregate productivity growth. Overall, the within-firm component of incumbent firms drives the evolution of aggregate productivity, especially after the 2008 financial crisis.

We further exploit the richness of the data and find that two-way traders, i.e. both exporters and importers, are the main contributors to aggregate productivity (growth). Interestingly, firm-size (in terms of employment) is not a determining factor of aggregate productivity compared to the internationalisation status of firms. Finally, we provide a multi-country extension of our analysis using a dataset containing manufacturing firms from 18-EU countries. On top of the previous results, we see that the within-firm component of firms from the North drives aggregate productivity of the manufacturing sector in Europe.

Results suggest that the reallocation of resources across Belgian manufacturing firms decreased over time. There is a growing literature which attempts to understand the drivers of resource missallocation across firms and how this translates to aggregate productivity growth. Hopenhayn (2014) provides a detailed literature review on this topic. The main idea is that various policies and institutions prevent firms from equating their marginal revenue products of inputs with their marginal costs. This, in turn, has implications for aggregate growth. For example, we observe a large increase in missalocation during the 2008 financial crisis. This suggests that, on top of other distortions prevalent in the market, financial constraints can be considered as a potential source of missalocation during that period.[6] However, our analysis can only provide suggestive evidence of potential distortions and is thus silent about their exact nature and taxonomy.

[5] Their result matches ours when considering the case of perfect competition in the output market.

[6] See Hopenhayn (2014) for a nice literature review on the relevance of financial constraints in explaining misallocation and selection.

In addition, we find that resource reallocation is not a sufficient mechanism to explain the evolution of aggregate productivity. For this reason we need to look at changes in the distribution of firm-level productivities. On average, firms increase their productivity over time, and those that are most successful are both more deeply engaged in internationalisation and larger in size. All other firms lag behind and prevent aggregate productivity from reaching its full potential. As indicated from our production function estimates, learning mechanisms are important in explaining differences in the evolution of the within firm component and thus aggregate productivity growth. The idea is that firms learn from their actions, i.e. trade. This suggest that theoretical modelling should move to more complex structures where static reallocation is combined with dynamic learning mechanisms. Overall, we expect our results to be insightful both for Belgium's and other European economies' efforts to deregulate and reduce frictions in response to increased global competition and stagnated economic activity.

With the above in mind, the remainder of this paper is organised as follows. Section 2.2 describes the empirical methodology and Section 2.3 describes the data. Section 2.4 presents an analysis of potential biases and the main results from the decompositions for different groups of firms. Finally, Section 2.5 offers concluding remarks.

2.2 Empirical Methodology

We discuss three important components of our methodology. First, we document the computation of aggregate productivity. This includes the choice of a productivity measure and estimator, and market share weights. Second, we motivate our choice for the decomposition method of aggregate productivity that is best suited for our analysis, and generalise it to account for the number of additional groups we consider. Third, we describe how to obtain standard errors for the decomposed components.

2.2.1 Productivity and Weights

The literature offers a number of alternative choices for productivity estimators and measures (ω_{it}), and for market share weights (s_{it}). Since aggregate productivity does not always represent productivity of the aggregate when certain assumptions fail to hold, there is no consensus on superior alternatives. Balk (2016) provides a detailed discussion of how specific choices can affect the decomposition of aggregate productivity. Overall, the choice ultimately depends on the research question and available data.

Following Bartelsman and Dhrymes (1998), Foster et al. (2001) and Collard-Wexler and De Loecker (2015), we base our analysis on measures of gross-output productivity and deflated nominal gross-output shares as weights.[7] We consider alternative productivity measures such as: labour productivity; total factor productivity under different assumptions in the output market; total factor productivity under different assumptions regarding the extent of common production technology across industries; and total factor productivity when facing sample restrictions. Using a given decomposition method and weights, we are then able to infer the implications of choosing specific productivity measures on aggregate productivity and its evolution.

We start with labour productivity (LP), defined as the share of output over labour.[8] We then switch to an estimate of total factor productivity assuming perfect competition in the output market (PC). This competing productivity index provides the closest approximation to disembodied technological change.[9] For the estimation, we consider a flexible gross-output production function $Y_{it} = F_{\kappa}(K_{it}, L_{it}, M_{it})\mathrm{e}^{\omega_{it}+\epsilon_{it}}$, with Hicks-neutral total factor productivity ω_{it} (herein TFP). In logs, the production function to be estimated is of the following form:

$$y_{it} = f_{\kappa}(k_{it}, l_{it}, m_{it}) + \omega_{it} + \epsilon_{it} \tag{2.1}$$

where y_{it}, k_{it} and m_{it} are log values of deflated (at the industry level) sales, beginning of the period capital stock, and material costs, respectively, and l_{it} is the log of the total number of full-time equivalent (FTE) employees of firm i in period t. κ represents the level of common production technology across firms $f_{\kappa}(\cdot)$, i.e. sector or industry. TFP is unobserved to the econometrician but known to the firm. Ex-post shocks, i.e. after the firm's decision on input use, are picked up by ϵ_{it}.

Capital is assumed to be predetermined and therefore chosen one period prior to the

[7] Using weights based on nominal gross-output or labour shares results are qualitatively robust.

[8] See Balk (2016) for a review of the potential biases induced when aggregating labour productivity.

[9] Most, if not all, estimates of total factor productivity are different from disembodied technological change, known as the 'Solow Residual' (Solow, 1957). They also include the impact of inputs that are not measured or available in the data (e.g. management practices and human capital skills). Results should be interpreted bearing this in mind.

realisation of TFP. Labour is assumed to be a dynamic input, meaning that it is variable in period t but has dynamic implications due to the presence of adjustment costs. Therefore, it is chosen during the realisation of TFP, i.e. between $t-1$ and t. The only flexible input is material that freely adjusts in each period and has no dynamic implications.[10]

Estimation of the production function is based on the two-step estimator proposed by Gandhi, Navarro, and Rivers (2016) (herein GNR). On top of the transmission bias, i.e. firms observing their productivity when choosing their inputs, this estimator controls for the value-added bias that arises from estimating a value-added rather than a gross-output production function. A detailed description of the assumptions, steps followed, and its dominance over competing estimators can be found in GNR.[11]

Similar to most proxy variable methods, this procedure identifies both production function parameters and the effects on current TFP (in expectation) of lagged observable actions of firm i in period t. In principle, we should control for any action or change in the firm's operating environment. However, due to data limitations we can control only for variables observed in the data. We expect trade to be the most important control especially when considering Belgium, a small open European economy during the latest financial and Eurozone crisis. Such controls are also internally consistent with the choice of firm attributes (e.g. trade and size) used for the decomposition analysis in the following section. For example, two-way traders represent firms most engaged in trade and largest in size (Mayer and Ottaviano, 2008).

For our specification we consider a controlled Markov process where, in addition to lagged TFP, we allow past experience from export (De Loecker, 2013), import (Kasahara and Rodrigue, 2008), and two-way trade to affect current TFP.[12] Following Aw et al. (2011) and De Loecker (2013) we use the following flexible parametric specification for

[10] Results are robust to the alternative assumption that labour is predetermined.

[11] See GNR for an exposition of the sizeable effects of value-added bias on productivity heterogeneity. In Chapter 3, my co-author and I stress the importance of such misspecification when estimating learning by doing effects.

[12] With lagged values, we inherently assume that it takes one period for actions to affect TFP. Such an assumption can be relaxed and tested for robustness against alternative specifications with deeper lags.

the productivity process:

$$\begin{aligned}\omega_{it} = &\sum_{j=1}^{4} \rho_j \omega_{it-1}^{j} + \rho_x x_{it-1} + \rho_m m_{it-1} + \rho_{xm} xm_{it-1} + \rho_{x\omega} x_{it-1}\omega_{it-1} \\ &+ \rho_{m\omega} m_{it-1}\omega_{it-1} + \rho_{xm\omega} xm_{it-1}\omega_{it-1} + \rho_t + \rho_s + \xi_{it}\end{aligned} \tag{2.2}$$

where x_{it-1}, m_{it-1} and xm_{it-1} are dummies reflecting whether a firm is an exporter, importer or two-way trader, respectively. These groups are mutually exclusive and the reference group of purely domestic firms is subsumed in the constant. Also, ρ_t and ρ_s are fixed-effects that account for relevant unobserved macroeconomic shocks and aggregate structural differences across industries, respectively.[13] ξ_{it} captures, unanticipated at $t-1$, exogenous shocks that affect firm's TFP in time t.

Based on estimates of the production function coefficients $\left(\hat{f}_{\kappa}(\cdot)\right)$ and ex-post shocks to production ($\hat{\epsilon}_{it}$), we can compute TFP ($\hat{\omega}_{it}$) and other relevant variables, i.e. output elasticities of inputs and returns to scale, for firm i in period t, using equation (2.1). In addition, using equation (2.2), we can also directly identify the effects on future TFP when engaging in international trade that can be causally interpreted as: learning by exporting $\left(\frac{\partial \omega_{it}}{\partial x_{it-1}}\right)$; learning by importing $\left(\frac{\partial \omega_{it}}{\partial m_{it-1}}\right)$; and learning by two-way trading $\left(\frac{\partial \omega_{it}}{\partial xm_{it-1}}\right)$.

With the available firm-level data, we do not observe physical output at the firm level, but only monetary values which we deflate at the industry level. Under the assumption of perfect competition in the output market of each industry, both LP and PC produce indices of physical productivity. However, under any type of imperfectly competitive output market structure, price differences across firms emerge. In this case, the productivity measures should be interpreted as revenue-based (Klette and Griliches, 1996).

To avoid potential price biases in aggregate productivity as shown in Foster et al. (2008), we estimate TFP controlling for unobserved variation in firm-specific prices. To do so, we circumvent the data limitations by introducing more structure and assumptions in the empirical model. This includes an iso-elastic demand system coupled with monopolistic competition, similar to De Loecker (2011).[14] However, the approach we follow is more

[13]Fixed effects enter additively in order to restrict the parameter space and improve the efficiency of the estimation. This should be considered with caution since non-linearities in the fixed-effects would saturate the model, resulting in incidental parameters bias.

[14]Note that we do not have data on multi-product firms and thus need to assume that each firm produces one unique variety.

flexible since it is able to identify time-varying instead of constant markups by assuming a CES demand system with time-varying elasticity of demand. This is expected to be insightful to the extent to which, on average, firms adjust their markups over time.

Under these assumptions the production function to be estimated is of the following form:

$$r_{it} = \left(\frac{\sigma_t + 1}{\sigma_t}\right) f_{\kappa}(k_{it}, l_{it}, m_{it}) - \frac{1}{\sigma_t} y_t + \left(\frac{\sigma_t + 1}{\sigma_t}\right) \omega_{it} + \chi_{it} + \left(\frac{\sigma_t + 1}{\sigma_t}\right) \epsilon_{it} \tag{2.3}$$

where r_{it} is the (observed in the data) log value of deflated sales at the industry level, given by $r_{it} = (p_{it} - p_t) + y_{it}$. p_{it} and p_t are the log values of the output price of firm i and the aggregate output deflator (aggregate price index), respectively. y_t is the log value of a quantity index serving as an aggregate demand shifter. This is computed using the log value of a simple average of deflated sales. χ_{it} captures firm specific demand shocks, σ_t is the time varying elasticity of demand derived from a generalised version of a CES demand system and $\frac{\sigma_t+1}{\sigma_t}$ is by construction the inverse of the markup. It is now straightforward to see that not accounting for price differences in the output market (i.e. PC) leads to estimates of both the production function parameters and productivity that are decreasing functions of any potential unobserved (heterogeneity in) markups.

To control for the price bias, we follow the estimation procedure proposed by GNR (see Appendix C4 of their paper) and provide estimates based on two different assumptions. Firms are either assumed to observe demand shocks post production (IC), or, alternatively, demand shocks are observed once firms make their input decisions ($ICalt$). The former is preferable, because it permits TFP to be identified separately from demand shocks and markups.

Note that this estimator is not a panacea; it is also based on assumptions that could potentially prove restrictive. For example, if the assumption for IC fails to hold then we end up with a productivity estimate where we cannot net out demand shocks, i.e. $\omega_{it} + (\frac{\sigma_t}{\sigma_t+1})\chi_{it}$, similar to $ICalt$, i.e. $(\frac{\sigma_t+1}{\sigma_t})\omega_{it} + \chi_{it}$. Nevertheless, given the data at hand, it is the best available alternative in terms of both the potential biases for which it corrects and its empirical robustness for identifying true TFP. We expect these two cases to be informative about the extent to which two seemingly similar assumptions, within the same estimation method, lead to different conclusions about aggregate productivity.

We also estimate TFP based on IC when excluding micro firms[15] ($ICsize$), in order to explore whether decompositions are sensitive to sample selection. A sample that drops small firms could potentially bias the impact of entry and exit on aggregate productivity (Foster et al., 2002). Finally, for each of the above cases, we consider two alternative levels (κ) of common production technology across firms $f_\kappa(\cdot)$. First, we estimate TFP by pooling all firms in the manufacturing sector ($Manuf$). Second, we estimate TFP by pooling firms in each industry ($Nace$) separately.[16] This allows us to examine the importance of properly accounting for differences in production technologies across industries on aggregate productivity.

TFP is a unitless measure. To guarantee that our measure is insensitive to measurement units and allows for transitive comparisons, we compare it to a reference firm at the start of the period (see Aw et al., 2001; Pavcnik, 2002; Van Biesebroeck, 2008). Therefore, all productivity measures used in the decompositions are expressed as the difference between each firm's estimated TFP and that of a reference firm with mean TFP in the same industry in the base period.

2.2.2 Decomposition of Aggregate Productivity

We define aggregate productivity (Ω_t), as the share weighted average of the log of firm productivity:[17]

$$\Omega_t = \sum_{i \in \Pi_t} s_{it}\omega_{it} \qquad \text{s.t.} \qquad \sum_{i \in \Pi_t} s_{it} = 1 \tag{2.4}$$

where $s_{it} = \sum_{i \in \Pi_t} \left(\frac{Y_{it}}{\sum_{i \in \Pi_t} Y_{it}} \right)$ is the share weight, Y is real output, and Π_t is the set of all active firms in each period.

Various methods to decompose aggregate productivity have been proposed. On the one hand, several decompositions examine the margins of aggregate productivity levels (static). On the other hand, a variety of decompositions focus on the sources of aggregate

[15]Less than 10 employees and up to €2 million operating revenue (European Commission, 2017).

[16]We use the A*38 industry classification that represents intermediate SNA/ISIC aggregation. See Table 2.A.1 in Appendix 2.A for correspondence with the NACE Rev.2 2-digit classification.

[17]The arithmetic mean of the logs is equivalent to the geometric mean of the levels. See Balk (2016) for a brief discussion on the implications of alternative aggregation methodologies. Melitz and Polanec (2015) derive and decompose the arithmetic mean of both the logs and levels of productivity. Results remain similar.

productivity growth (dynamic).[18]

We follow the widely used method of Olley and Pakes (1996) (OP), where productivity is decomposed into two components in each period:

$$\Omega_t = \frac{1}{N_t}\sum_{i\in\Pi_t}\omega_{it} + \sum_{i\in\Pi_t}(s_{it}-\bar{s}_t)(\omega_{it}-\bar{\omega}_t) = \bar{\omega}_t + cov(s_{it},\omega_{it}) \tag{2.5}$$

where N_t is the number of elements in Π_t, $\bar{\omega}_t$ is the unweighted average of productivity (within-firm), and $cov(s_{it}, \omega_{it})$ is the covariance between market share and productivity (between-firm). The latter is of particular policy interest since it is considered as an indicator of underlying mechanisms of aggregate productivity (growth). For example, for the case of a deregulation of the US telecommunications equipment industry, OP interpret higher values of the covariance term as a reallocation of resources to the most productive firms. Similarly, Bartelsman et al. (2013) provide evidence that lower values indicate the presence of market distortions induced by policies, which can explain productivity differences across countries.

On the one hand, Balk (2016) describes the covariance term as a 'statistical artefact' that does not necessarily represent key microeconomic mechanisms. On the other hand, Maliranta and Määttänen (2015) provide both empirical and theoretical evidence that the covariance term performs well when capturing important distortions, i.e. output tax and subsidy scheme, compared to others, i.e. entry and exit costs. Therefore, we need to use theoretical models that capture the extent to which certain types of distortions explain differences in the marginal value of inputs across firms. Hopenhayn (2014) provides a detailed review of such models and summarises their relevance in explaining productivity gaps. Overall, we interpret the covariance term as a measure of resource (mis)allocation, bearing in mind that it most likely does not capture all potential market distortions and even if it does we will not be able to identify their exact nature and taxonomy.

It is straightforward to extend the decomposition for a number of disjunct groups:

$$\Omega_t = \sum_{j=\Psi_t} s_{jt}\left(\sum_{i\in\Pi_{jt}}\frac{s_{it}}{s_{jt}}\omega_{it}\right) = \sum_{j=\Psi_t} s_{jt}\Omega_{jt} \qquad \text{s.t.} \qquad \sum_{j=\Psi_t} s_{jt} = 1 \tag{2.6}$$

[18]See Melitz and Polanec (2015) for an empirical comparison between their approach and various dynamic decomposition methods.

where the set Ψ_t defines the abbreviations of the names of the mutually exclusive groups considered $\big($i.e. $\bigcup_{j\in\Psi_t}\Pi_{jt}=\Pi_t$ and $\bigcap_{j\in\Psi_t}\Pi_{jt}=\emptyset\big)$, s_{jt} is the aggregate market share of group j, and Ω_{jt} is group j's aggregate productivity.

To measure the contribution of each group on aggregate productivity, we use a reference group $\mathcal{A}_t \subset \Psi_t$. This way, in each period, we can express the aggregate productivity contribution of the complement group(s) $\mathcal{A}_t^c$ as:

$$\Omega_t = \Omega_{\mathcal{A}_t t} + \sum_{j=\mathcal{A}_t^c} s_{jt}\big(\Omega_{jt} - \Omega_{\mathcal{A}_t t}\big) \tag{2.7}$$

where $\mathcal{A}_t \cap \mathcal{A}_t^c = \Psi_t$.[19]

To understand whether the aggregate productivity of different groups is driven by changes in the average productivity or reallocation of resources within each group relative to the reference group, we insert (2.5) into (2.7):

$$\Omega_t = \bar{\omega}_{\mathcal{A}_t t} + cov_{\mathcal{A}_t}(s_{it},\omega_{it}) + \sum_{j=\mathcal{A}_t^c}\Bigg[s_{jt}\Big(\bar{\omega}_{jt} - \bar{\omega}_{\mathcal{A}_t t}\Big) + s_{jt}\Big(cov_j(s_{it},\omega_{it}) - cov_{\mathcal{A}_t}(s_{it},\omega_{it})\Big)\Bigg] \tag{2.8}$$

where, for each group j, $\bar{\omega}_{jt} = \frac{1}{N_{jt}}\sum\limits_{i\in\Pi_{jt}}\omega_{it}$ is its unweighted average productivity and $cov_j(s_{it},\omega_{it}) = \sum\limits_{i\in\Pi jt}\left(\frac{s_{it}}{s_{jt}} - \frac{\sum_{i\in\Pi jt}\frac{s_{it}}{s_{jt}}}{N_{jt}}\right)\left(\omega_{it} - \bar{\omega}_{jt}\right)$ is the covariance between its market share and productivity.[20]

On the one hand, our main focus is on the cross-sectional importance of the productivity distribution of different groups of firms, i.e. entry and exit, trade, size, geography, and combinations of those, on the aggregate.[21] Therefore, we compute equation (2.7) and (2.8) for each period in the dataset.

On the other hand, we are also interested in the contribution of certain groups of firms

[19]To motivate their analysis, Maliranta and Määttänen (2015) use this specification to identify the contribution of non-staying firms on aggregate productivity.

[20]Maliranta and Määttänen (2015) use a transformation of this equation, defined as 'Augmented Static OP Productivity Decomposition', to study how entering and exiting firms contribute to the covariance term. Collard-Wexler and De Loecker (2015) define this equation as 'within technology' decomposition and combine it with a 'between technology' transformation of the OP decomposition. Their goal is to explain changes in aggregate productivity through changes within and across two vintage technologies in the steel industry.

[21]See Maliranta and Määttänen (2015) for a discussion on the importance of static measures on understanding the components of aggregate productivity growth.

to aggregate productivity growth. In this case, due to compositional changes between firms over time, the literature suggests a variety of dynamic decomposition methods, spanning from the seminal contribution of Baily et al. (1992) to the most recent one of Melitz and Polanec (2015). However, if we look carefully, our analysis so far is sufficient to directly identify the contribution of certain groups. For example, for the case of surviving, entering and exiting firms, the terms in brackets in equation (2.8) are analogous to the terms considered in the 'Dynamic OP Decomposition' developed by Melitz and Polanec (2015). Therefore, when considering entering firms, they can be directly interpreted as the contribution of entering firms on aggregate productivity growth.[22] Finally, for all other groups, the yearly differences of each component in equation (2.8) can be interpreted as approximate percentage contributions to productivity growth.[23]

2.2.3 Statistical Inference

The empirical literature on the micro-level determinants of aggregate productivity has typically assessed the relevance of the components of aggregate productivity on the basis of visual inspections. However, this approach casts doubts on the validity of the results since it is not based on formal statistical inference. Even though the decomposition is an exact procedure, i.e. analysis of variance, there is inherent uncertainty induced. As in any empirical work, the analysis is based on micro-level data. Even in the case of accessing census datasets covering the full population, the analysis will still be subject to sampling error.[24]

To take this uncertainty into account, formal statistical inference is needed. However, with few exceptions, most of the empirical literature is silent about these issues. Foster et al. (2006) create a regression analogue to both decompose productivity growth in components for continuing, exiting and entering firms, and provide estimates for their

[22] Since in a dynamic context exit is forward looking, we can interpret the minus of exitor's ($\mathcal{A}^c$) $t-1$ counterpart from equation (2.8) as the contribution of exiting firms to aggregate productivity growth. For the contribution of surviving firms, we can use the yearly differences in the reference group $\mathcal{A}_t$ plus their counterpart in brackets for exiting firms ($\mathcal{A}^c$), as shown in equation (2.8).

[23] We under(over)-estimate when exiting firms in the group of interest have lower(higher) aggregate productivity compared to surviving firms. The magnitude of the bias depends on the relative importance of each group in terms of market shares.

[24] Note that any of the productivity measures used in the decompositions are either computed or estimated and therefore susceptible to measurement error. See Hausman (2001) for a short review on the potential biases induced from mismeasured left hand side variables in econometric analysis. However, as is typical in the decomposition literature, this is something we do not account for in our methodology.

standards errors, respectively. Collard-Wexler and De Loecker (2015) retrieve standard errors after bootstrapping the decomposed components of aggregate productivity growth along the TFP estimation procedure.

To address this issue we follow the procedure introduced by Hyytinen, Ilmakunnas, and Maliranta (2016) (henceforth HIM). This regression-based method allows us to retrieve point estimates with autocovariance and heteroscedasticity-robust standard errors for each component in the OP decomposition. The idea is based on the dissection of a simple regression:

$$E[\omega_{it}|s_{it}] = E[\omega_{it}] + cov(s_{it}, \omega_{it})var(s_{it})^{-1}\big(s_{it} - E[s_{it}]\big) \tag{2.9}$$

that reveals the potential for estimating the components of an OP decomposition using an ordinary least squares (OLS) regression. A pooled OLS regression of firm productivity on a full set of time dummies and scaled[25] share weights gives estimates for both the within and between component in each period. The point estimates are numerically equivalent to the right hand side components in equation (2.5) and the standard errors are autocovariance and heteroscedasticity-robust.

Following HIM, with the relevant scaling of the regressors, we extend this approach to account for the mutually exclusive groups considered in equation (2.8). Overall, we retrieve a time-series of point estimates, with their respective confidence intervals, that we illustrate in time-line charts for an easier interpretation.

2.3 Data

We use the Annual Accounts, VAT declarations and Transactions Trade dataset from the National Bank of Belgium (NBB). The combined dataset is representative of the Belgian manufacturing sector with detailed information on the balance sheet and trade activities of individual firms.

We focus on the sample of Belgian active manufacturing[26] firms that file unconsolidated accounts[27] over the period 1998-2012. We retain firms reporting sales, capital stock at

[25] Demeaned shares weights over the cross sectional variance times the number of firms in each period.

[26] Table 2.A.1 in Appendix 2.A provides an overview of the NACE Rev.2 2-digit industries and their correspondence to the more aggregate A*38 code that represents intermediate SNA/ISIC aggregation.

[27] This refers to accounts not integrating the statements of possible controlled subsidiaries or branches of the concerned company.

the start of the period, number of employees in FTE, material costs, and exporting and importing status.We remove outliers using the BACON method proposed by Billor et al. (2000).[28] The manufacture of coke and refined petroleum products (19) is removed, due to the insufficient number of observations for estimating TFP at the industry level. Overall, we end up with an unbalanced panel of 21643 firms and 178695 observations for the period 1998-2012 (see Table 2.1 for summary statistics for the firm-level variables in the sample).

Table 2.1: Summary Statistics

	Obs.	Mean	St.Dev.	p25	p50	p75
Sales^a	178695	10855	87434	382	1048	3754
Capital stock^a	178695	1699	12843	62	218	696
Material costs^a	178695	8542	74713	218	665	2630
Employment in FTE	178695	35	159	2.4	6.8	21
Surviving	178695	.94	.24	1	1	1
Entering^b	178695	.034	.18	0	0	0
Exiting	178695	.026	.16	0	0	0
Experimenting	178695	.0015	.038	0	0	0
Domestic	178695	.56	.5	0	1	1
Exporting	178695	.064	.25	0	0	0
Importing	178695	.1	.3	0	0	0
Two-way-Trading	178695	.27	.44	0	0	1

Notes: ^{a} monetary variables in thousand Euro, ^{b} includes Experimenting firms. NBB database for 21643 manufacturing firms from 1998 to 2012.

We need to deflate monetary variables using the appropriate NACE Rev.2 2-digit output deflator from the EU KLEMS database to estimate TFP. Real output (Y) is sales deflated with producer price indices. Capital (K) is tangible fixed assets deflated by the average of the deflators of various NACE Rev.2 2-digit industries (Javorcik, 2004b).[29] Real material inputs (M) is material inputs deflated by an intermediate input deflator constructed as a weighted average of output deflators, where country-time-industry specific weights are based on intermediate input uses retrieved from input-output tables. Labour (L), is the number of employees in FTE.

For the decomposition analysis we construct dummy variables which classify the firms in mutually exclusive groups to be considered in each period. On the one hand, *Surviving*,

[28] BACON stands for Block Adaptive Computationally efficient Outlier Nominators. It is a multiple outlier detection method. The variables considered in the method are log of output, labour, capital and material.

[29] Electrical equipment (27); machinery and equipment n.e.c. (28); motor vehicles, trailers and semi-trailers (29); and other transport equipment (30).

includes the firms that exist both in $t-1$ and $t+1$. *Entering* is a backward looking variable and considers the firms that do not exist in $t-1$ but exist in t. Inversely, *Exiting* is a forward looking variable and takes the value of 1 when firms are present in t, but not in $t+1$. *Experimenting* consists of firms that appear only in t. Since the latter group represents only 0.15% of the total sample, i.e. approximately 5% of entrants, we incorporate it in the *Entering* group.[30] Therefore, we end up with three mutually exclusive groups of firms: *Surviving*; *Entering*; and *Exiting*.[31]

On the other hand, when considering trade, *Domestic*, *Exporting*, *Importing* and *Two-way-trading*, are mutually exclusive dummy variables indicating whether, at each point in time, a firm is purely domestic, exporting, importing, or both exporting and importing, respectively. We see that 44% of the sample engages in some type of trade activity, which is consistent with Belgium's economic history as a small and heavily trade oriented economy.

2.4 Results

In this section we first assess the importance of various productivity indices for a given decomposition method and share weights. Then, based on the most competitive case, we analyse the components of aggregate productivity in detail. Finally, we provide a multi-country extension of our analysis using a pan-European dataset.

2.4.1 Productivity Indices

Production Function Estimates. Table 2.2 presents the production function estimates for the cases discussed in Section 2.2.1, i.e. PC, IC, $ICalt$ and $ICsize$. In the first column, under perfect competition in the output market, firms face decreasing returns to scale (RTS). In the presence of price differences across firms, output elasticities of inputs and thus RTS will be biased downward since we only observe sales deflated at the industry level (Klette and Griliches, 1996). The size of the bias is an increasing function of the inverse of the markup. Columns 2 and 3 confirm the existence of such a bias. Compared to column 1, all estimated output elasticities have higher values that

[30] This choice is made in order to reduce the complexity of the analysis. It does not distort the contribution of entering firms in the decompositions.

[31] Note that the variables are constructed based on information from the initial sample.

result in increasing RTS. This is the outcome when firms charge higher prices that exceed their marginal costs.[32]

Table 2.2: Production Function Estimates

	(1) PC	(2) IC	(3) $ICalt$	(4) $ICsize$
$\bar{\hat{\theta}}^k_{it}$	0.062***	0.070***	0.070***	0.063***
	(0.002)	(0.003)	(0.003)	(0.007)
$\bar{\hat{\theta}}^l_{it}$	0.267***	0.297***	0.296***	0.268***
	(0.002)	(0.003)	(0.003)	(0.009)
$\bar{\hat{\theta}}^m_{it}$	0.633***	0.710***	0.710***	0.756***
	(0.002)	(0.005)	(0.005)	(0.020)
$\bar{\hat{RTS}}_{it}$	0.963***	1.077***	1.076***	1.086***
	(0.002)	(0.006)	(0.006)	(0.029)
$\bar{\hat{RTS}}_{it} - 1$	-0.037***	0.077***	0.076***	0.086***
	(0.002)	(0.006)	(0.006)	(0.029)
$\bar{\hat{Markup}}_t$		1.121***	1.121***	1.104***
		(0.006)	(0.006)	(0.028)
Learning by ...				
$Exporting_{it-1}$	0.002***	0.003***	0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$Importing_{it-1}$	0.004***	0.004***	0.004***	0.003***
	(0.000)	(0.001)	(0.001)	(0.001)
$Two\text{-}way\text{-}Trading_{it-1}$	0.003***	0.004***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	154637	154088	154088	69565

Notes: * $p < 0.05$, ** $p \leq 0.01$, *** $p < 0.001$. Each column is estimated using all manufacturing firms. $\bar{\hat{\theta}}^k_{it}$, $\bar{\hat{\theta}}^l_{it}$ and $\bar{\hat{\theta}}^m_{it}$ are averages of the estimated output elasticities of capital, labour and material respectively. $\bar{\hat{RTS}}_{it}$ is the average of the estimated RTS. $\bar{\hat{Markup}}_t$ is the average of the estimated annual markups. The lower panel gives the average, of the estimated in equation (2.2), effects on future TFP from exporting, importing and two-way trading. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

Note that, even though the estimator in column 3 does not separate TFP from markups and demand shocks, results are similar to those in column 2. Since markups only vary over time, time variation is captured by the aggregate yearly demand shifter in the production

[32] Multiplying any of the estimated output elasticities and RTS in columns 2-3 with the inverse of their respective markup leads approximately to the estimates of column 1.

function (2.2) and the time fixed effects in the Markov process (2.3). Therefore, coefficients for the estimated production function and Markov process are fairly similar. Nevertheless, this does not imply that TFP estimates from IC and $ICalt$ are similar, since the latter entails variation in markup and demand shocks, i.e. $\left(\frac{\sigma_t+1}{\sigma_t}\right)\omega_{it} + \chi_{it}$. Results hold when estimating any of the previous cases for each industry separately (see Tables 2.A.3-2.A.6 in Appendix 2.A).

In the lower panel of Table 2.2, we find that firms learn from international trade, i.e. *Exporting* (De Loecker, 2013), *Importing* (Kasahara and Rodrigue, 2008) and *Two-way-trading*. To our knowledge, the latter effect has not been reported in the literature. However, it is an intuitive result, since firms that engage in exporting and importing are more likely to benefit from both activities. In addition, there appears to be a ranking in terms of the learning effects. Be it at the fourth decimal, the long-run[33] learning effects range from 4.60% for *Two-way-trading* firms to 3.65% for *Exporting* firms (see Table 2.A.2 in Appendix 2.A). This suggests that, in the long run, firms that both export and import benefit the most from internationalisation.

Performing the analysis per industry reveals that this pattern is only significant in a few industries (see Tables 2.A.3-2.A.6 in Appendix 2.A). This is in line with Lileeva and Trefler (2010), where the heterogeneous productivity impact from exporting is explained by a firm's initial productivity level as well as differential effects from investing.This result can also be reconciled by the fact that a large share of Belgian manufacturing firms export products that they do not produce, i.e. Carry-Along Trade (Bernard et al., 2012). Therefore, the potentials of learning by exporting are expected to vary across firms depending on the nature of trade. Overall, heterogeneity in the result emphasises the importance of controlling for technological differences across industries, i.e. estimating production functions at a more disaggregated level where firms are technologically more uniform.

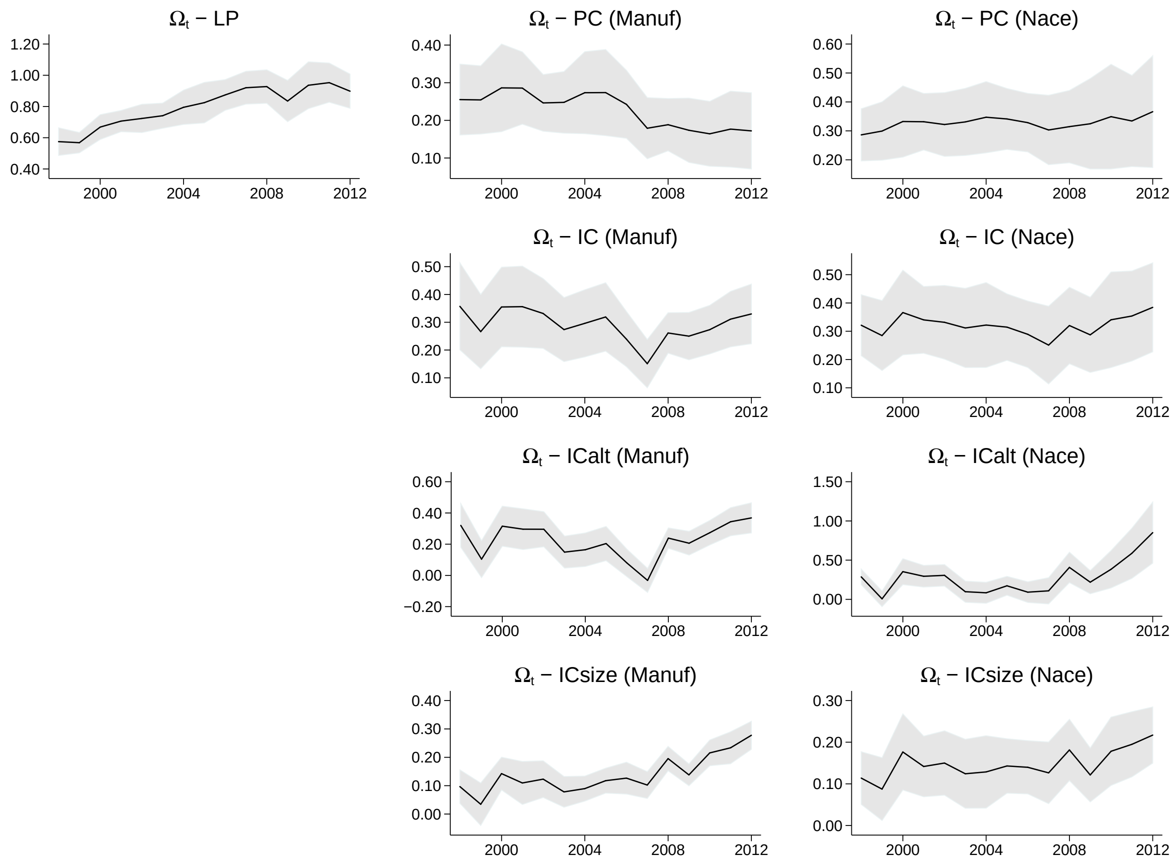
Note that the learning effects reported above point to the potential determinants of future productivity. At first glance this could be considered sufficient to describe the drivers of aggregate productivity growth. However, aggregate productivity is a share weighted average of firm-level productivity indices. Even if the determinants of firm-

[33]The long-run effects are calculated using estimates from equation (2.2). Each effect is computed as the product of the average short-run effects on future TFP from exporting, importing and two-way trading times $1/(1-\rho) * 100$, where ρ is the average persistence of TFP.

level productivity are known, this is not the case for the share weights used to compute aggregate productivity. Overall, these results can be informative only for the determinants of the within component of aggregate productivity. As such, we need to explore each of the components of aggregate productivity further.

Aggregate Productivity. In Figure 2.1, we compare the evolution of aggregate productivity under various assumptions, estimators, and samples. The top left panel uses simple labour productivity. We find that aggregate productivity has been increasing for the Belgian manufacturing sector since 1998, with a temporary downturn during the financial crisis in 2008 and the Euro-zone crisis in 2011. However, this trend is inconsistent with the other alternatives we consider.

Figure 2.1: Annual aggregate productivity.



Notes: Authors' calculations. Ω_t is the share weighted average of the logarithm of productivity with deflated nominal sales as weights. The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval following the procedure of HIM.

When comparing the second and third columns, we see that even a seemingly 'trivial assumption,' i.e. the aggregation of firms in groups, can bias the measure of aggregate productivity. Intuitively, as pointed out earlier, there is heterogeneity in the production technology across industries. If not properly accounted for, i.e. in the second column, TFP estimates mismeasure the contribution of certain industries on the aggregate. This reiterates the importance of estimating production functions at a more disaggregated level. Therefore, even within the same TFP estimator, different assumptions about the environment in which firms operate can lead to significantly different predictions.

Further, in the third column, trends in aggregate productivity are found to be distorted when price differences in the output market are not accounted for, i.e. PC differs from IC.[34] This suggests that firms adjust their prices when hit by shocks, which is an important element both at the micro and aggregate levels. Notice that the two middle panels in column 3 reveal patterns that are reasonably similar. However, the micro-mechanisms behind these aggregate fluctuations may differ. For example, TFP estimates under $ICalt$ also include demand shocks and markups that potentially drive the components of aggregate productivity in a different way than under IC.

2.4.2 Decomposition

OP Decomposition. In Figure 2.2 we decompose aggregate productivity and only consider TFP measures that are based on production functions estimated at the industry level, i.e. $Nace$. Each row contains panels for aggregate productivity (first column) and an OP decomposition with a within-firm (second column) and a between-firm (third column) component. Shaded areas represent autocovariance and heteroscedasticity robust 95% confidence intervals (by year). The last column plots estimated markups for the cases of imperfect competition considered.

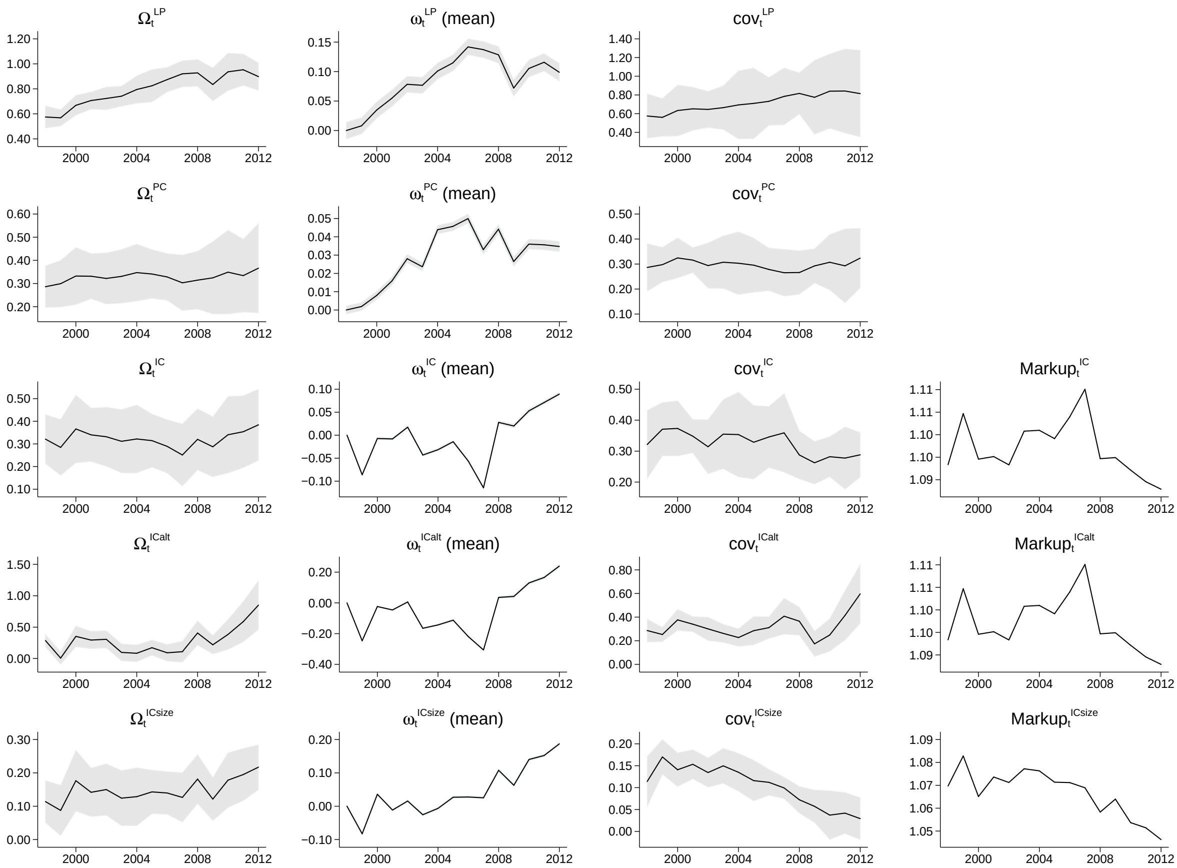
We see a sharp decline in markups during the financial crisis in 2008 which lasts until 2012 when economic and political uncertainty in the Eurozone prevailed. This provides suggestive evidence that markups are an important margin of adjustment for firms in the presence of shocks.[35] Such an adjustment is expected to be prevalent in the decomposition analysis of aggregated micro-units. This becomes clear when we compare the first two

[34] Foster et al. (2008) are the first to report this result. They mainly focus on how price differences across plants affect the contribution of entering and exiting firms on aggregate productivity growth.

[35] Our analysis can accommodate only time-varying markups that vary across industries but not across firms within industries. Therefore, we are unable to elaborate on incomplete pass-through (Melitz and Ottaviano, 2008; De Loecker et al., 2016). However, the analysis is sufficient to highlight the distortive capacity of markups on the decomposition of aggregate productivity.

rows (in which we do not control for price differences) with the other rows. The trends are sufficiently different to illustrate that it is imperative to control for such price differences in the estimation procedure (Foster et al., 2008).

Figure 2.2: Aggregate productivity, OP decomposition and markups.



Notes: Authors' calculations. Ω_t is the share weighted average of the logarithm of productivity with deflated nominal sales as weights and is the sum of the components in the second and third columns. All TFP measures are based on production functions estimated at the industry level ($Nace$). The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval, for each point estimate of the OP decomposition, following the procedure of HIM. Markup is the average across industries of estimated markups in each year.

In the third and forth rows we see that seemingly 'minor' differences in a certain set of assumptions may have a considerable impact even within the same estimation procedure. In the forth row, from 2009 onwards there is a vast increase in the covariance term. This is interpreted as an 'improvement' in the reallocation mechanism, which is in line with the within-firm component contributing positively to the evolution of aggregate productivity during that period. However, the row above suggests a relatively constant reallocation process. This discrepancy is generated by the fact that the TFP measure used in the forth row, $\tilde{\omega}_{it} = \left(\frac{\sigma_t+1}{\sigma_t}\right)\omega_{it} + \chi_{it}$, is an increasing function of ω_{it} (true TFP as identified in the third row), $\frac{\sigma_t+1}{\sigma_t}$ (inverse of markup) and χ_{it} (demand shocks). When the markup decreases, $\tilde{\omega}_{it}$ increases and hence, from the properties of the covariance, the between-firm component increases mechanically.

Finally, the last row of Figure 2.2–which uses a similar estimation procedure as the third row but excludes micro firms which account for more than half of the sample–shows that using a restricted sample might skew results and lead to incorrect conclusions. To correct for the biases described above, we proceed with the decomposition analysis for TFP estimated using the IC procedure on an industry-by-industry basis for all firms in the sample.

Entry and exit. In Figure 2.3 we consider a decomposition for the following groups of firms: *Surviving* (S); *Entering* (EN); and *Exiting* (EX). The group of surviving firms is taken as the basis, whereas entering and exiting firms are shown relative to this group in the second and third rows, respectively. Summing both components of the OP decomposition, i.e. mean (second column) and covariance (third column), gives the aggregate productivity for each group (first column).

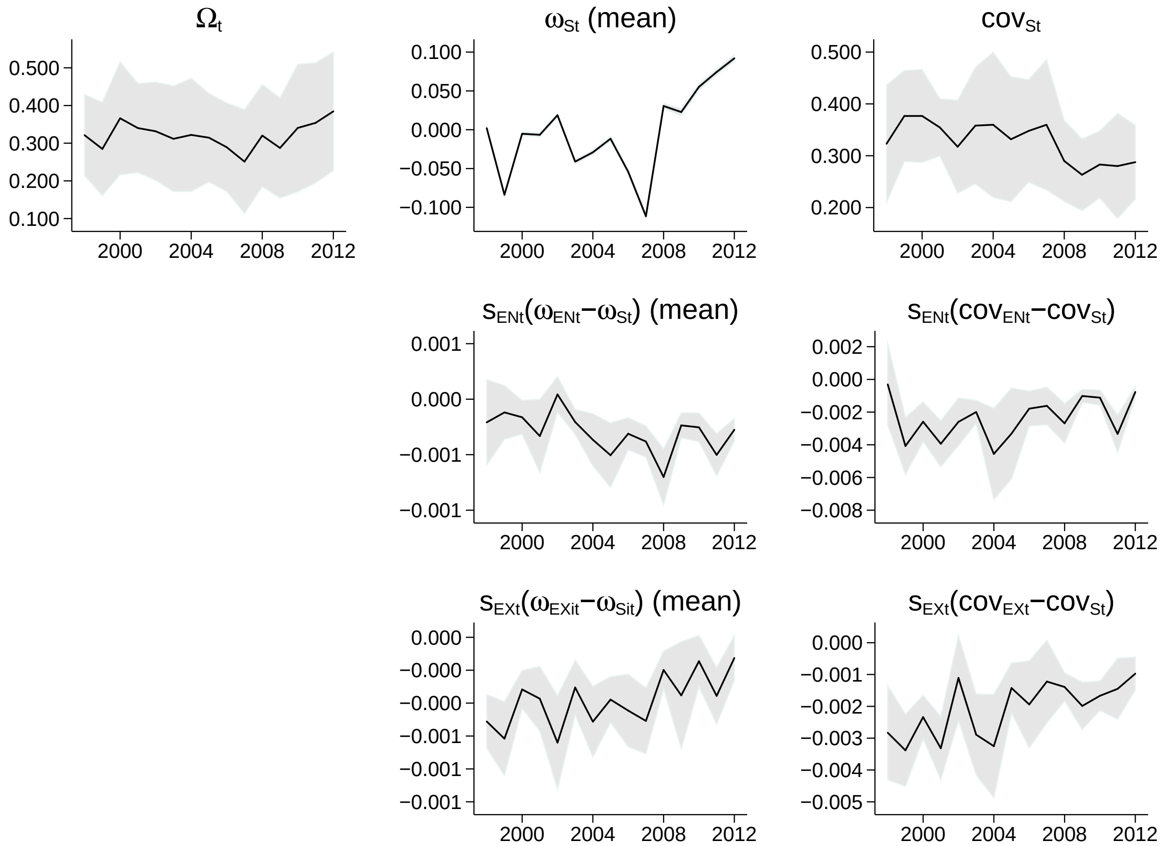
The last two rows show negative contributions of groups EN and EX on aggregate productivity relative to S. If EN had not entered and EX had exited earlier, aggregate productivity at time t would have been on average 0.52% higher. On the one hand, if firms are to exit in $t+1$, they depress aggregate productivity in the present period. Once they exit, aggregate productivity increases by roughly 0.25%. This is because their current aggregate productivity is, on average, lower compared to the group of surviving firms. On the other hand, entering firms (EN) reduce aggregate productivity (growth) by 0.27% due to their lower aggregate productivity compared to incumbent (S) firms.

The gaps in the aggregate productivity of groups EX and EN relative to S are mainly driven by the differences in the covariance term. In the last row, the gaps in both components of the OP decomposition have been narrowing over time for the group of exiting firms. These gaps have remained fairly stable over time for entering firms.[36] This suggests that the group of exiting firms, unlike the entering ones, were relatively more productive near the end of the sample period and thus contributed less to overall

[36] Melitz and Polanec (2015) report similar results when decomposing aggregate productivity growth in Slovenia with their preferred decomposition method. The results can also be reconciled with the concept of dynamic selection introduced by Sampson (2016).

productivity growth.

Figure 2.3: OP decomposition with entry and exit.



Notes: Authors' calculations. Ω_t is the share weighted average of TFP with deflated nominal sales as weights and is the sum of all of the components in the second and third columns. TFP is computed from a production function estimated under IC at the industry level ($Nace$). The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval, for each point estimate of the OP decomposition, following the procedure of HIM.

In absolute terms, the contribution of both EN and EX on aggregate productivity (growth)[37] has been small because of their small market shares. This confirms earlier findings by Foster et al. (2008), Maliranta and Määttänen (2015) and Melitz and Polanec (2015) for US manufacturing, the Finish business sector, and Slovenian manufacturing, respectively. Overall, *Surviving* firms in the Belgian manufacturing sector are responsible for the bulk of aggregate productivity (growth).[38] This result is not surprising given Belgium's level of economic development.

[37]See aggregate productivity growth in Figure 2.A.1 in Appendix 2.A.

[38]Note that both entry and exit are defined on a yearly basis. Therefore, fast growing young firms of high potential are expected to be in the *Surviving* category of our sample. Dumont et al. (2016) find that across the EU, surviving entrants gradually become more efficient and contribute positively to aggregate productivity growth.

Both the mean and covariance components of the group of surviving firms (S) are important determinants of the evolution of aggregate productivity.[39] Interestingly, they started moving in opposite directions from the start of the financial crisis in 2008. The average productivity of group S in 2007 shifts from a slowly decreasing trend to an increasing one. There is a clear upward trend when we exclude micro firms (see Figure 2.A.2 in Appendix 2.A). This suggests that a big part of the variation is driven by micro firms which seem more responsive to changes in their operating environment. These firms are on average less productive and represent more than half of the sample.

The relationship between market shares and productivity has weakened over time, with a considerable drop from 2007 onwards. This suggests that an increase in the presence of resource misallocation prevented the Belgian manufacturing sector from reaching its full potential. Van Beveren and Vanormelingen (2014) use the same dataset for the period 1997-2009 and find that resource reallocation is a positive and stable contributor to aggregate productivity growth. However, their estimates do not control for price bias and results are driven by changes in markups. This can be seen from the fact that our results in column PC in Figure 2.2 qualitatively verify their reported estimates for the respective period. Overall, after the outbreak of the financial crisis, the increase in average productivity of incumbent firms dominated the increase in the misallocation of resources, and determined aggregate productivity (growth).

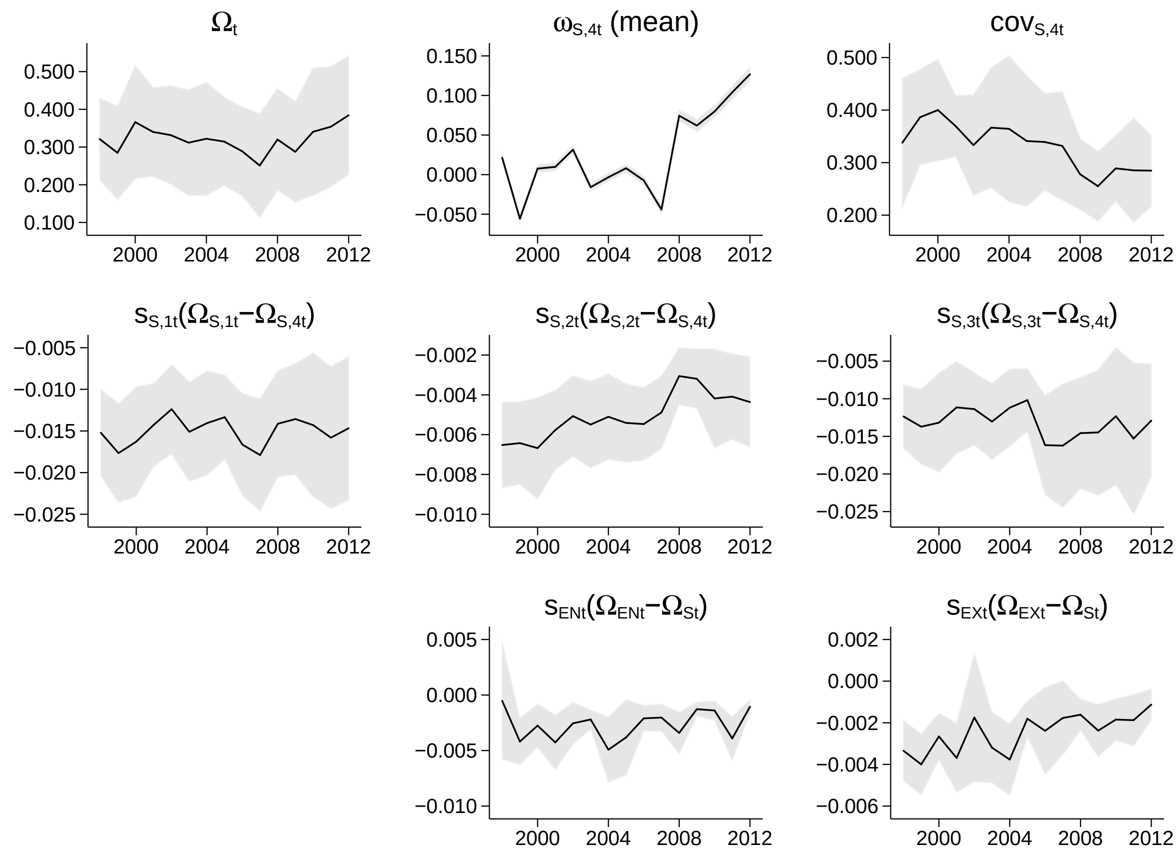
Trade. In Figure 2.4 we further decompose surviving firms in four mutually exclusive groups based on their engagement in international trade: *Domestic* $(S, 1)$; *Exporting* $(S, 2)$; *Importing* $(S, 3)$; and *Two-way-trading* $(S, 4)$ firms. Figure 2.4 shows that predominantly incumbent two-way traders determine the evolution of aggregate productivity. The trends of the OP components for group $S, 4$ are in line with those for group S in the previous figure. The other groups lag behind, but for exporting survivor firms $(S, 2)$ we observe some signs of convergence up to 2007 followed by a divergence thereafter.

It appears that firms that exclusively export were more affected by the financial and Euro-zone crisis than *Two-way-trading*. These firms are likely not diversified in terms of exporting destinations and therefore suffer more from any negative macroeconomic

[39] For further empirical support on the mean component see: Foster et al. (2008). For further empirical support on the covariance component see: Aw et al. (2001); Foster et al. (2001, 2006); and Melitz and Polanec (2015).

shocks. In the Mayer et al. (2014) context, in response to trade/macroeconomic events, these firms need to skew their sales towards their better performing products in order to increase their productivity. However, for *Exporting* firms this adjustment is expected to be smaller compared to *Two-way-trading* firms, since, in the case of Belgium, they are relatively small firms that sell less products to fewer countries (Bernard et al., 2014). Therefore, the scope for adjustment in the product margin is limited for these firms.

Figure 2.4: OP decomposition with entry, exit and trade

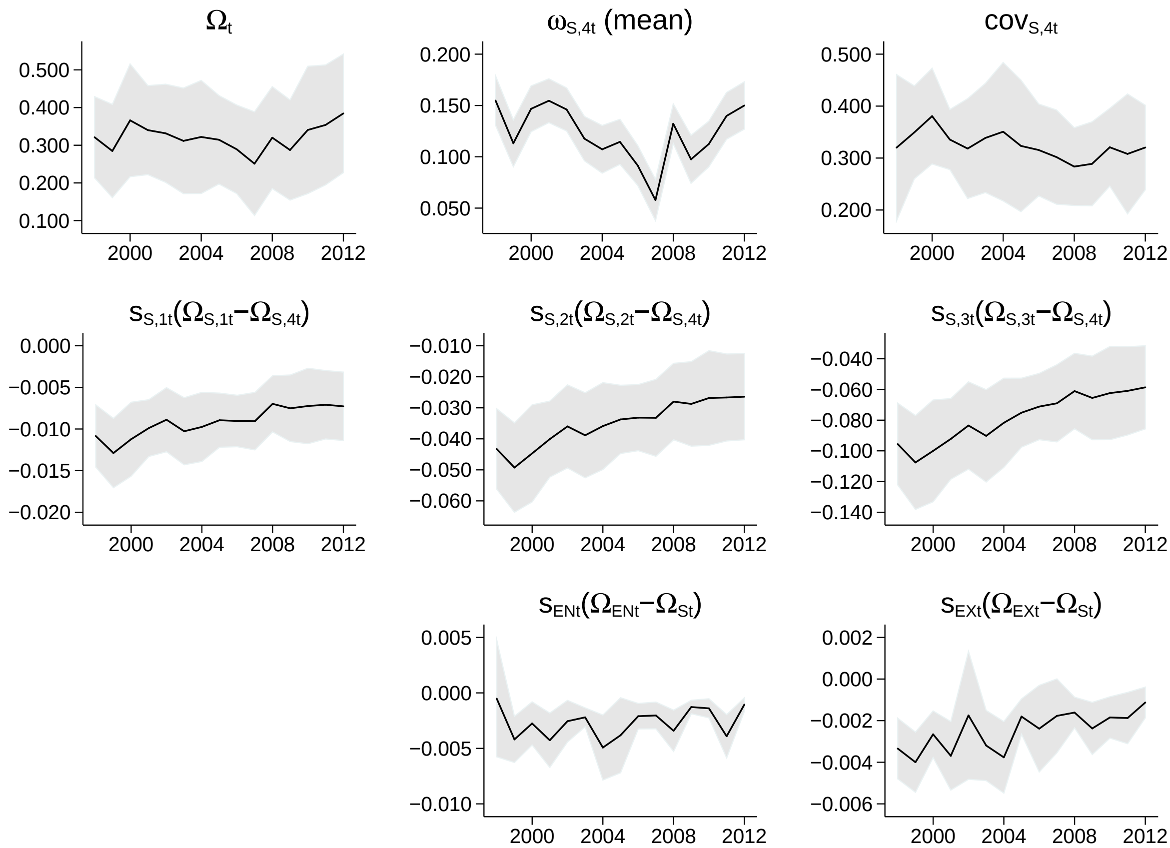


Notes: Authors' calculations. Ω_t is the share weighted average of TFP with deflated nominal sales as weights and is the sum of all other components in the panel. TFP is computed from a production function estimated under *IC* at the industry level (*Nace*). The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval, for each point estimate of the OP decomposition, following the procedure of HIM.

Size. In Figure 2.5 we decompose the set of surviving firms in size-based mutually exclusive groups. Four size categories are determined using the EU's definition that depends on staff headcount and turnover criteria (European Commission, 2017): *Micro* $(S, 1)$; *Small* $(S, 2)$; *Medium* $(S, 3)$; and *Large* $(S, 4)$. We find that *Large* firms drive aggregate productivity, while other size groups remain relatively unproductive. This result is in line with findings of significant TFP differences between small and large firms in

Van Biesebroeck (2005). Interestingly, the less productive *Micro*, *Small* and *Medium* groups follow a similar path of convergence over time.

Figure 2.5: OP decomposition with entry, exit and size

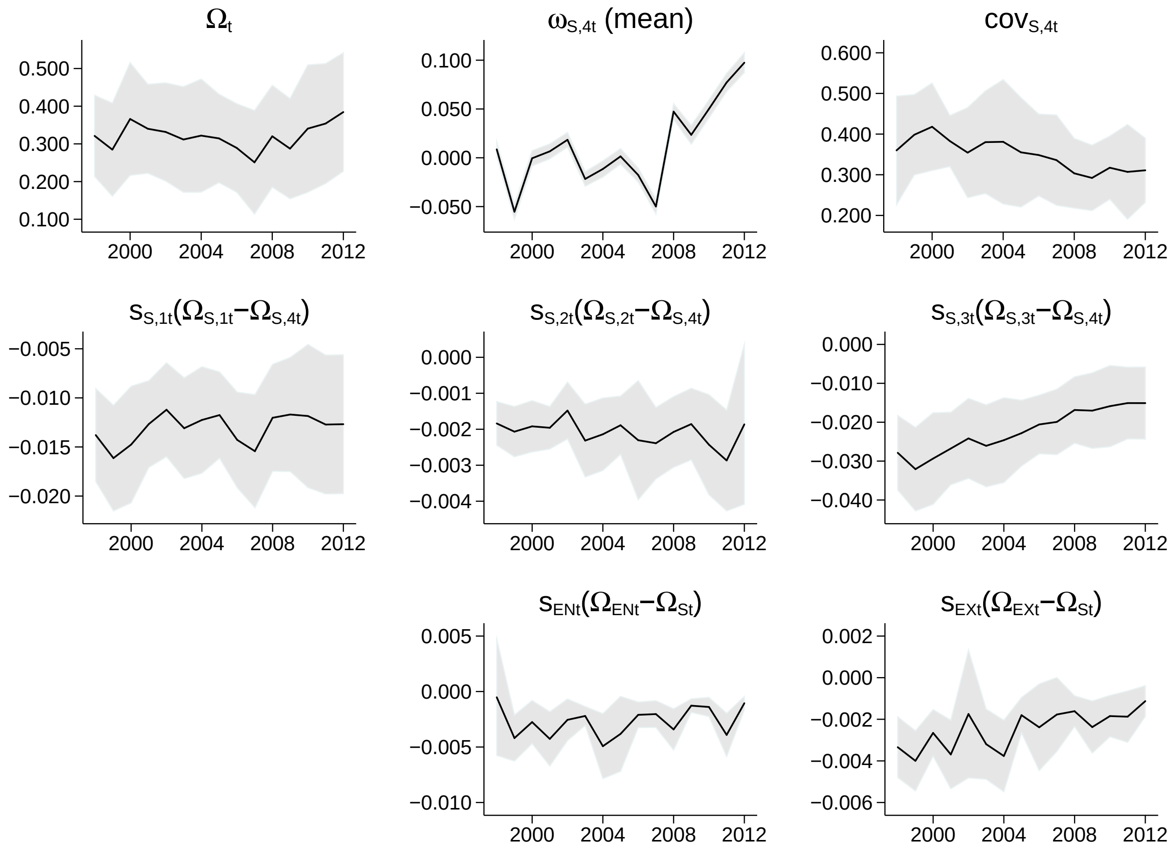


Notes: Authors' calculations. Ω_t is the share weighted average of TFP with deflated nominal sales as weights and is the sum of all other components in the panel. TFP is computed from a production function estimated under *IC* at the industry level (*Nace*). The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval, for each point estimate of the OP decomposition, following the procedure of HIM.

Trade and Size. Results presented in Figure 2.5 potentially mask heterogeneity induced by further firm-characteristics. Therefore, we unravel potential heterogeneity in size groups in Figure 2.6 by splitting the set of surviving firms in four mutually exclusive groups, based on size and trade activity: *Small & Domestic* $(S, 1)$; *Large & Domestic* $(S, 2)$; *Small & Trade* $(S, 3)$; and *Large & Trade* $(S, 4)$.[40] From Figure 2.6 it is clear that group $S, 4$ determines the evolution of aggregate productivity. This is in line with the majority of exports being accounted for by few exporting firms that have more employees and are on average more productive than smaller exporters (Bernard et al., 2014).

[40] *Small* refers to firms with less than 50 employees and at least €10 million turnover, and *Large* includes the rest of the firms in the sample. *Trade* includes any type of trade activity, i.e. firms that are

Figure 2.6: OP decomposition with entry, exit, trade and size



Notes: Authors' calculations. Ω_t is the share weighted average of TFP with deflated nominal sales as weights and is the sum of all other components in the panel. TFP is computed from a production function estimated under IC at the industry level ($Nace$). The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval, for each point estimate of the OP decomposition, following the procedure of HIM.

In the second row, we see that the convergence trend described above is existent only for the group of non-domestic firms. This confirms that the trends for smaller-sized firms above were driven by other firm characteristics. Over time, the increase in the within-firm component for this group of firms dominates the decrease in the contribution of the between-firm component. Overall, this translates to large firms that engage in international trade undergoing a substantial increase in their productivity, despite lower levels of resource reallocation. Our results indicate the importance of international trade in shaping aggregate productivity (growth) for a small open economy such as Belgium.

not *Domestic*.

2.4.3 Extensions

We extend the analysis by focusing on different factors that could drive aggregate productivity. To proceed, we use a firm-level panel of manufacturing firms for 18 EU countries[41] during the period 2002-2012 (see Appendix 2.B for further details on the construction and summary statistics of the data). We estimate TFP using the *IC* procedure for each industry by pooling all countries available in the dataset. Once again, we confirm the presence of significant biases in the decomposition analysis when not controlling for the price bias in TFP estimates (see Figure 2.C.1 in Appendix 2.C).

EU and Size. As before, we split the surviving firms in groups based on their size (see Figure 2.C.2 in Appendix 2.C). Similar patterns emerge to those in Figure 2.5. Large firms are the main contributors to aggregate European productivity (growth). Average firm-productivity has increased substantially over the years and dominated the decreasing trend in the reallocation mechanism. These results suggest that Europe is facing a period of extended resource misallocation in the manufacturing sector that does not allow aggregate productivity to reach its potential. All remaining groups show similar signs of convergence to the case of Belgium.

EU and Geography. In Figure 2.7 we exploit the geographical dimension in our dataset and split the set of surviving firms into four mutually exclusive groups: *Late-East* $(S, 1)$; *East* $(S, 2)$; *South* $(S, 3)$; and $North$ $(S, 4)$. These dimensions do not only refer to physical geography, but also embed economic and institutional characteristics that are prevalent among certain groups of countries.[42]

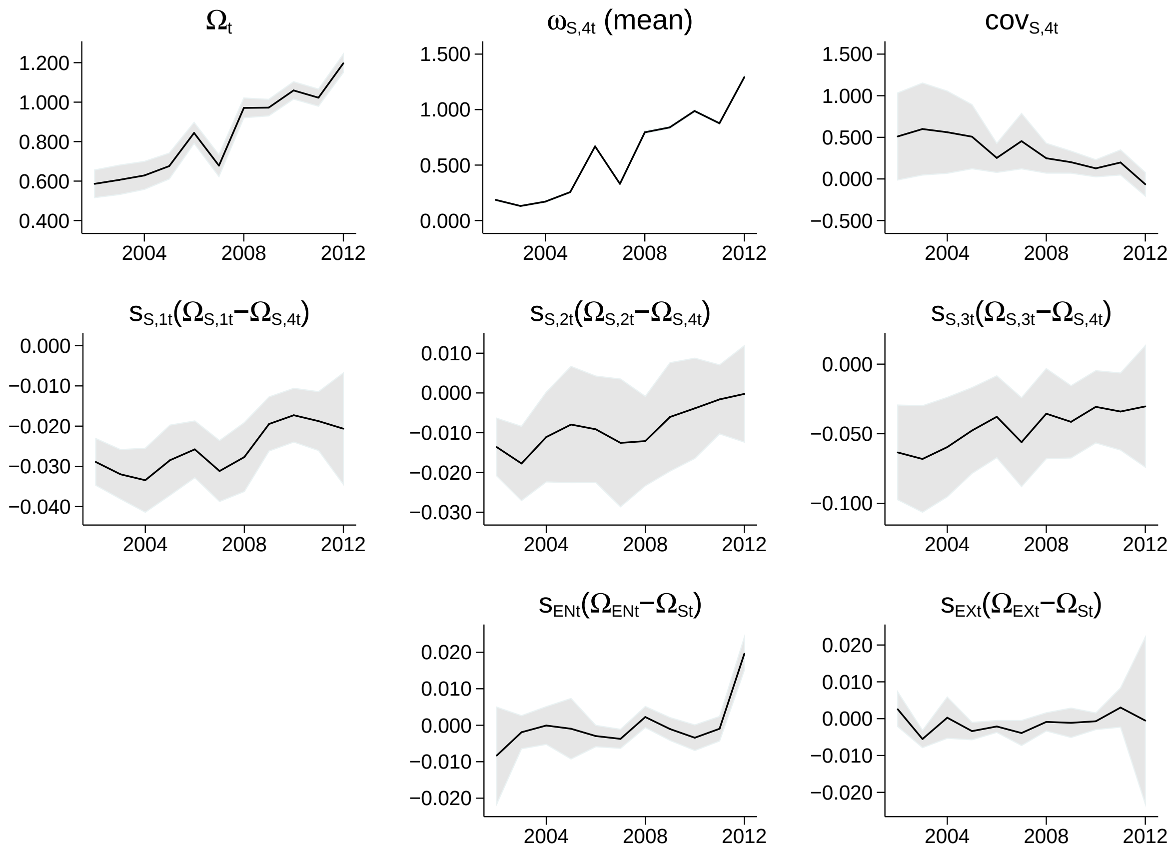
Despite a continuous increase in the misallocation of resources in manufacturing, $North$ has been driving aggregate productivity in the EU through a substantial increase in its average productivity. *Late-East* and *South* have been consistently lagging behind $North$, but show signs of convergence. The interesting trend is for the *East* group. Until EU accession in 2004, *East*'s contribution to aggregate productivity was significantly lower than $North$'s. This is no longer the case after EU accession. Eastern European countries

[41] This includes: Austria (AT); Belgium (BE); Bulgaria (BG); Germany (DE); Estonia (EE); Spain (ES); Finland (FI); France (FR); Croatia (HR); Hungary (HU); Italy (IT); Netherlands (NL); Poland (PL); Portugal (PT); Romania (RO); Sweden (SE); Slovenia (SI); and Slovakia (SK).

[42] *Late-East* includes the countries that are legally bound to join the Schengen Area but implementation has been delayed, i.e. BG, HR and RO. *East* includes the Central-Eastern European countries: EE; LV; PL; SI; and SK. *South* includes: ES; IT; and PT. Finally, $North$ includes: AT; BE; DE; FI; FR; NL; and SE.

went through an extensive period of restructuring that attracted capital flows. As such, the economy benefited not only from the presence of foreign direct investment, but also from productivity spillovers to the local economy. Overall, after the EU enlargement of 2004, the productivity of the *East* group was on average comparable to that of the *North* and influenced aggregate productivity in the EU. Clearly, this result could be entirely driven by the presence of multinationals that represent the biggest share of aggregate productivity in these economies.

Figure 2.7: OP decomposition with entry, exit and geography in EU



Notes: Authors' calculations. Ω_t is the share weighted average of TFP with deflated nominal sales as weights and is the sum of all other components in the panel. TFP is computed from a production function estimated under IC at the industry level ($Nace$) pooling all EU countries together. The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval, for each point estimate of the OP decomposition, following the procedure of HIM.

2.5 Conclusion

The evolution of aggregate productivity is an important determinant of economic growth. A large literature has tried to understand the micro-origins of aggregate productivity and various methods for its computation and decomposition have been put forth. However, there is substantial heterogeneity in reported results, mainly for two reasons. First, biased firm-level productivity measures skew aggregate productivity. Second, certain firm attributes that determine aggregate productivity growth remain uncovered.

In this paper we account for these cases and estimate TFP under various assumptions. As such, we assess the biases by contrasting different productivity measures for a given decomposition method and weights. After controlling for such biases, we introduce a new dimension in the decomposition based on firm attributes. This allows us to assess whether there is a handful of firms driving aggregate productivity.

For the analysis, we use a detailed firm-level dataset for the Belgian manufacturing sector, over the period 1998-2012. Our results can be summarised as follows. First, we demonstrate and confirm important biases arising from ignoring output-price differences across firms, estimating physical productivity under different assumptions (i.e. timing of demand shocks, estimating production functions at the manufacturing instead of the industry level, and selection of samples with larger firms). Failing to correct for these biases may thus result in false conclusions about the evolution of aggregate productivity and its decomposed components.

Second, after controlling for such biases, we find that the reallocation of resources across firms has been steadily decreasing since 1998, with a rapid drop during the 2008 financial crisis. Inversely, we find that the decreasing trend in average firm-productivity reversed during the 2008 financial crisis. Overall, the within-firm component of incumbent firms drives the evolution of aggregate productivity, especially after the 2008 financial crisis.

We exploit the richness of the data, and find that two-way traders are the main contributors of aggregate productivity (growth). It appears that learning is an important mechanism in explaining such productivity differences over time. Interestingly, firm-size (in terms of employment) is not a determining factor of aggregate productivity compared to the internationalisation of firms. Finally, we provide a multi-country extension of our analysis using a dataset containing manufacturing firms from 18-EU countries. About and beyond to the previous results, we see that the within-firm component of firms from the North is driving aggregate productivity of the manufacturing sector in Europe.

Firms increase their productivity over time and those that are most successful are larger in size and more deeply engaged in internationalisation. All other firms lag behind and prevent aggregate productivity from reaching its full potential. Knowing which type of firms have significantly been driving the economy or suffering during good and bad times is expected to provide policymakers and institutions with a strong reference point for shaping future policies.

Appendix 2.A Additional Figures and Tables

Table 2.A.1: List of NACE Rev.2 2-digit industries in the manufacturing sector.

A*38	Division	Description
CA	10	Manufacture of food products
CA	11	Manufacture of beverages
CA	12	Manufacture of tobacco products
CB	13	Manufacture of textiles
CB	14	Manufacture of wearing apparel
CB	15	Manufacture of leather and related products
CC	16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
CC	17	Manufacture of paper and paper products
CC	18	Printing and reproduction of recorded media
CE	20	Manufacture of chemicals and chemical products
CF	21	Manufacture of basic pharmaceutical products and preparations
CG	22	Manufacture of rubber and plastic products
CG	23	Manufacture of other non-metallic mineral products
CH	24	Manufacture of basic metals
CH	25	Manufacture of fabricated metal products, except machinery & equip.
CI	26	Manufacture of computer, electronic and optical products
CJ	27	Manufacture of electrical equipment
CK	28	Manufacture of machinery and equipment n.e.c.
CL	29	Manufacture of motor vehicles, trailers and semi-trailers
CL	30	Manufacture of other transport equipment
CM	31	Manufacture of furniture
CM	32	Other manufacturing
CM	33	Repair and installation of machinery and equipment

Note: A*38 code refers to the intermediate SNA/ISIC aggregation.

Table 2.A.2: Long-run Effects from Learning by Trading

	(1)	(2)	(3)	(4)
Learning by ... in %	PC	$ICalt$	IC	$ICsize$
$Exporting_{it-1}$	1.78***	3.65***	3.09***	0.96
$Importing_{it-1}$	4.15***	4.51***	4.16***	3.60***
$Two\text{-}way\text{-}trading_{it-1}$	2.87***	4.60***	4.24***	4.09***

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The long-run effects are calculated using estimates from equation (2.2). Each column is computed as the product of the average short-run effects on future TFP from exporting, importing and two-way trading times $1/(1-\rho)*100$; where ρ is the average persistence of TFP. Each column is estimated using all firms in the manufacturing sector. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure.

Table 2.A.3: Production Function Estimates under PC

	NACE Rev.2, A*38 SNA/ISIC aggregation											
	CA	CB	CC	CE	CF	CG	CH	CI	CJ	CK	CL	CM
$\bar{\hat{\theta}}_{it}^{k}$	0.057***	0.067***	0.054***	0.046***	-0.005	0.051***	0.048***	0.037***	0.030***	0.031***	0.040***	0.049***
	(0.003)	(0.004)	(0.004)	(0.011)	(0.032)	(0.005)	(0.003)	(0.010)	(0.008)	(0.005)	(0.012)	(0.004)
$\bar{\hat{\theta}}_{it}^{l}$	0.232***	0.251***	0.267***	0.231***	0.290***	0.242***	0.307***	0.304***	0.280***	0.284***	0.249***	0.265***
	(0.004)	(0.006)	(0.009)	(0.015)	(0.048)	(0.006)	(0.006)	(0.011)	(0.012)	(0.007)	(0.014)	(0.005)
$\bar{\hat{\theta}}_{it}^{m}$	0.640***	0.647***	0.624***	0.716***	0.663***	0.668***	0.600***	0.579***	0.641***	0.652***	0.695***	0.618***
	(0.003)	(0.005)	(0.003)	(0.007)	(0.012)	(0.004)	(0.003)	(0.007)	(0.007)	(0.004)	(0.008)	(0.004)
$R\bar{\hat{T}}S_{it}$	0.929***	0.966***	0.944***	0.994***	0.948***	0.961***	0.955***	0.919***	0.951***	0.966***	0.984***	0.932***
	(0.003)	(0.005)	(0.007)	(0.010)	(0.032)	(0.005)	(0.005)	(0.009)	(0.009)	(0.005)	(0.010)	(0.004)
$R\bar{\hat{T}}S_{it} - 1$	-0.071***	-0.034***	-0.056***	-0.006	-0.052*	-0.039***	-0.045***	-0.081***	-0.049***	-0.034***	-0.016	-0.068***
	(0.003)	(0.005)	(0.007)	(0.010)	(0.032)	(0.005)	(0.005)	(0.009)	(0.009)	(0.005)	(0.010)	(0.004)
Learning by ...												
$Exporting_{it-1}$	0.006***	0.004	-0.001	0.014	0.024	0.002	0.002**	0.007	-0.332***	-0.000	-0.002	0.000
	(0.001)	(0.003)	(0.001)	(0.009)	(0.038)	(0.002)	(0.001)	(0.006)	(0.004)	(0.002)	(0.005)	(0.002)
$Importing_{it-1}$	0.004***	0.008***	0.004***	0.012*	0.005	0.003***	0.002**	0.006	-0.210***	0.006***	0.001	0.004**
	(0.001)	(0.002)	(0.001)	(0.007)	(0.042)	(0.001)	(0.001)	(0.004)	(0.003)	(0.002)	(0.003)	(0.001)
$Two\text{-}way\text{-}Trading_{it-1}$	0.005***	0.010***	0.006***	0.006	0.007	0.004***	0.002*	0.008***	-0.907***	0.001	-0.002	0.006***
	(0.001)	(0.001)	(0.001)	(0.009)	(0.032)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.006)	(0.001)
Observations	30187	11622	24119	4757	836	15617	32006	3938	3397	9710	2974	13730

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all firms in the respective industry. $\bar{\hat{\theta}}_{it}^{k}$, $\bar{\hat{\theta}}_{it}^{l}$ and $\bar{\hat{\theta}}_{it}^{m}$ are averages of the estimated output elasticities of capital, labour and material respectively. $R\bar{\hat{T}}S_{it}$ is the average of the estimated RTS. The lower panel gives the average, of the estimated in equation (2.2), effects on future TFP from exporting, importing and two-way trading. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

Table 2.A.4: Production Function Estimates under IC

	NACE Rev.2, A*38 SNA/ISIC aggregation											
	CA	CB	CC	CE	CF	CG	CH	CI	CJ	CK	CL	CM
$\bar{\hat{\theta}}^k_{it}$	0.064***	0.077***	0.069***	0.054***	0.025	0.047***	0.050***	0.059***	0.037***	0.036***	0.039**	0.063***
	(0.003)	(0.006)	(0.004)	(0.011)	(0.050)	(0.008)	(0.004)	(0.010)	(0.011)	(0.006)	(0.016)	(0.004)
$\bar{\hat{\theta}}^l_{it}$	0.252***	0.283***	0.286***	0.232***	0.332***	0.264***	0.329***	0.323***	0.293***	0.304***	0.275***	0.306***
	(0.005)	(0.009)	(0.006)	(0.017)	(0.070)	(0.008)	(0.005)	(0.013)	(0.015)	(0.008)	(0.019)	(0.007)
$\bar{\hat{\theta}}^m_{it}$	0.705***	0.725***	0.692***	0.763***	0.694***	0.723***	0.654***	0.628***	0.690***	0.699***	0.759***	0.693***
	(0.005)	(0.012)	(0.007)	(0.010)	(0.022)	(0.008)	(0.004)	(0.010)	(0.012)	(0.007)	(0.018)	(0.008)
$R\bar{\hat{T}}S_{it}$	1.022***	1.085***	1.046***	1.049***	1.050***	1.034***	1.032***	1.010***	1.020***	1.038***	1.073***	1.062***
	(0.006)	(0.015)	(0.009)	(0.014)	(0.047)	(0.013)	(0.006)	(0.013)	(0.019)	(0.009)	(0.024)	(0.013)
$R\bar{\hat{T}}S_{it} - 1$	0.022***	0.085***	0.046***	0.049***	0.050	0.034***	0.032***	0.010	0.020	0.038***	0.073***	0.062***
	(0.006)	(0.015)	(0.009)	(0.014)	(0.047)	(0.013)	(0.006)	(0.013)	(0.019)	(0.009)	(0.024)	(0.013)
$Mar\bar{\hat{k}}up_t$	1.102***	1.120***	1.108***	1.063***	1.046***	1.082***	1.089***	1.088***	1.078***	1.073***	1.092***	1.123***
	(0.006)	(0.015)	(0.010)	(0.009)	(0.028)	(0.011)	(0.004)	(0.010)	(0.016)	(0.009)	(0.021)	(0.013)
Learning by ...												
$Exporting_{it-1}$	0.009***	0.006*	-0.001	0.017**	0.072	0.002	0.002*	0.015**	0.002	-0.000	0.004	0.002
	(0.001)	(0.003)	(0.001)	(0.007)	(0.230)	(0.002)	(0.001)	(0.008)	(0.004)	(0.003)	(0.006)	(0.002)
$Importing_{it-1}$	0.008***	0.011***	-0.001	0.008	0.083	0.002	0.002*	0.018***	0.005	0.008***	0.007	0.006***
	(0.002)	(0.002)	(0.001)	(0.006)	(0.155)	(0.002)	(0.001)	(0.006)	(0.004)	(0.002)	(0.005)	(0.002)
$Two\text{-}way\text{-}Trading_{it-1}$	0.010***	0.011***	0.001	0.000	0.056	0.001	-0.000	0.023***	0.003	0.002	0.016**	0.009***
	(0.002)	(0.003)	(0.001)	(0.008)	(0.067)	(0.002)	(0.001)	(0.004)	(0.004)	(0.002)	(0.006)	(0.002)
Observations	30187	11636	24052	4764	836	15629	32032	3938	3397	9702	2954	13726

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all firms in the respective industry. $\bar{\hat{\theta}}^k_{it}$, $\bar{\hat{\theta}}^l_{it}$ and $\bar{\hat{\theta}}^m_{it}$ are averages of the estimated output elasticities of capital, labour and material respectively. $R\bar{\hat{T}}S_{it}$ is the average of the estimated RTS. $Mar\bar{\hat{k}}up_t$ is the average of the estimated annual markups. The lower panel gives the average, of the estimated in equation (2.2), effects on future TFP from exporting, importing and two-way trading. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

Table 2.A.5: Production Function Estimates under $ICalt$

	NACE Rev.2, A*38 SNA/ISIC aggregation											
	CA	CB	CC	CE	CF	CG	CH	CI	CJ	CK	CL	CM
$\bar{\hat{\theta}}^k_{it}$	0.064***	0.077***	0.069***	0.054***	0.025	0.049***	0.062***	0.057***	0.045***	0.038***	0.039***	0.063***
	(0.003)	(0.006)	(0.004)	(0.011)	(0.056)	(0.005)	(0.003)	(0.010)	(0.011)	(0.006)	(0.014)	(0.004)
$\bar{\hat{\theta}}^l_{it}$	0.255***	0.283***	0.286***	0.232***	0.332***	0.262***	0.329***	0.328***	0.300***	0.305***	0.275***	0.306***
	(0.005)	(0.009)	(0.006)	(0.017)	(0.070)	(0.008)	(0.005)	(0.013)	(0.015)	(0.008)	(0.019)	(0.008)
$\bar{\hat{\theta}}^m_{it}$	0.705***	0.725***	0.692***	0.763***	0.694***	0.723***	0.654***	0.629***	0.691***	0.699***	0.759***	0.693***
	(0.005)	(0.012)	(0.007)	(0.010)	(0.022)	(0.008)	(0.004)	(0.010)	(0.012)	(0.007)	(0.018)	(0.008)
$R\bar{\hat{T}}S_{it}$	1.024***	1.085***	1.046***	1.049***	1.050***	1.035***	1.045***	1.013***	1.036***	1.042***	1.073***	1.062***
	(0.006)	(0.015)	(0.009)	(0.014)	(0.052)	(0.011)	(0.005)	(0.013)	(0.018)	(0.009)	(0.023)	(0.013)
$R\bar{\hat{T}}S_{it} - 1$	0.024***	0.085***	0.046***	0.049***	0.050	0.035***	0.045***	0.013	0.036*	0.042***	0.073***	0.062***
	(0.006)	(0.015)	(0.009)	(0.014)	(0.052)	(0.011)	(0.005)	(0.013)	(0.018)	(0.009)	(0.023)	(0.013)
$Mar\bar{\hat{k}}up_t$	1.102***	1.120***	1.108***	1.063***	1.046***	1.083***	1.089***	1.089***	1.078***	1.073***	1.092***	1.123***
	(0.006)	(0.015)	(0.010)	(0.009)	(0.028)	(0.011)	(0.004)	(0.010)	(0.016)	(0.009)	(0.021)	(0.013)
Learning by ...												
$Exporting_{it-1}$	0.007***	0.005	-0.001	0.016**	0.071	0.001	0.001	0.009	0.001	-0.001	0.002	0.002
	(0.001)	(0.003)	(0.001)	(0.008)	(0.051)	(0.002)	(0.001)	(0.007)	(0.004)	(0.002)	(0.005)	(0.002)
$Importing_{it-1}$	0.006***	0.010***	-0.000	0.008	0.086*	0.002	0.000	0.008	0.004	0.006***	0.004	0.005***
	(0.001)	(0.002)	(0.001)	(0.006)	(0.050)	(0.002)	(0.001)	(0.006)	(0.004)	(0.002)	(0.005)	(0.002)
$Two\text{-}way\text{-}Trading_{it-1}$	0.009***	0.009***	0.001	-0.002	0.062	0.002	-0.002	0.010*	0.000	0.001	0.011*	0.007***
	(0.001)	(0.002)	(0.001)	(0.007)	(0.050)	(0.002)	(0.001)	(0.005)	(0.003)	(0.002)	(0.006)	(0.001)
Observations	30187	11636	24052	4764	836	15629	32032	3938	3397	9702	2954	13726

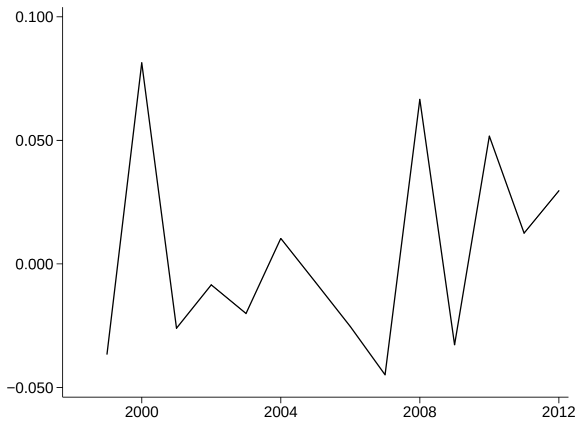
Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all firms in the respective industry. $\bar{\hat{\theta}}^k_{it}$, $\bar{\hat{\theta}}^l_{it}$ and $\bar{\hat{\theta}}^m_{it}$ are averages of the estimated output elasticities of capital, labour and material respectively. $R\bar{\hat{T}}S_{it}$ is the average of the estimated RTS. $Mar\bar{\hat{k}}up_t$ is the average of the estimated annual markups. The lower panel gives the average, of the estimated in equation (2.2), effects on future TFP from exporting, importing and two-way trading. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

Table 2.A.6: Production Function Estimates under $ICsize$

	NACE Rev.2, A*38 SNA/ISIC aggregation											
	CA	CB	CC	CE	CF	CG	CH	CI	CJ	CK	CL	CM
$\bar{\hat{\theta}}^k_{it}$	0.076***	0.052***	0.057***	0.063***	0.008	0.053***	0.058***	0.003	0.042***	0.024***	0.028	0.047***
	(0.005)	(0.010)	(0.008)	(0.016)	(0.091)	(0.007)	(0.007)	(0.029)	(0.012)	(0.006)	(0.018)	(0.005)
$\bar{\hat{\theta}}^l_{it}$	0.197***	0.257***	0.282***	0.192***	0.299	0.227***	0.322***	0.326***	0.291***	0.313***	0.240***	0.257***
	(0.008)	(0.019)	(0.018)	(0.023)	(0.316)	(0.009)	(0.012)	(0.046)	(0.033)	(0.012)	(0.025)	(0.012)
$\bar{\hat{\theta}}^m_{it}$	0.799***	0.742***	0.737***	0.762***	0.684***	0.729***	0.683***	0.694***	0.701***	0.690***	0.795***	0.707***
	(0.007)	(0.033)	(0.037)	(0.011)	(0.239)	(0.012)	(0.015)	(0.027)	(0.058)	(0.011)	(0.041)	(0.018)
$R\bar{\hat{T}}S_{it}$	1.072***	1.051***	1.076***	1.017***	0.991**	1.008***	1.064***	1.022***	1.034***	1.027***	1.062***	1.012***
	(0.009)	(0.048)	(0.050)	(0.019)	(0.419)	(0.015)	(0.022)	(0.052)	(0.087)	(0.014)	(0.056)	(0.026)
$R\bar{\hat{T}}S_{it} - 1$	0.072***	0.051	0.076	0.017	-0.009	0.008	0.064***	0.022	0.034	0.027*	0.062	0.012
	(0.009)	(0.048)	(0.050)	(0.019)	(0.419)	(0.015)	(0.022)	(0.052)	(0.087)	(0.014)	(0.056)	(0.026)
$Ma\bar{\hat{r}}kup_t$	1.078***	1.087***	1.092***	1.026***	1.025***	1.031***	1.077***	1.073***	1.065***	1.039***	1.104***	1.051***
	(0.007)	(0.048)	(0.054)	(0.012)	(0.357)	(0.015)	(0.023)	(0.039)	(0.086)	(0.013)	(0.053)	(0.025)
Learning by ...												
$Exporting_{it-1}$	0.003*	0.012	0.001	0.008	-0.010	-0.002	0.001	-0.014	-0.002	-0.003	0.002	-0.002
	(0.002)	(0.224)	(0.115)	(0.014)	(0.420)	(0.002)	(0.001)	(0.024)	(0.052)	(0.003)	(0.322)	(0.002)
$Importing_{it-1}$	0.001	0.010	0.001	-0.006	0.027	0.000	0.001	0.012	0.005	0.002	0.007	0.007***
	(0.001)	(0.084)	(0.149)	(0.009)	(0.166)	(0.001)	(0.001)	(0.016)	(0.126)	(0.002)	(0.174)	(0.002)
$Two\text{-}way\text{-}Trading_{it-1}$	0.002	0.014	0.000	-0.010	0.015	-0.002	-0.000	0.024	0.004	0.002	0.009	0.007***
	(0.002)	(0.062)	(0.105)	(0.010)	(0.253)	(0.001)	(0.001)	(0.015)	(0.125)	(0.002)	(0.080)	(0.002)
Observations	11551	6424	8753	3420	643	8714	13995	1574	1886	5144	1775	5128

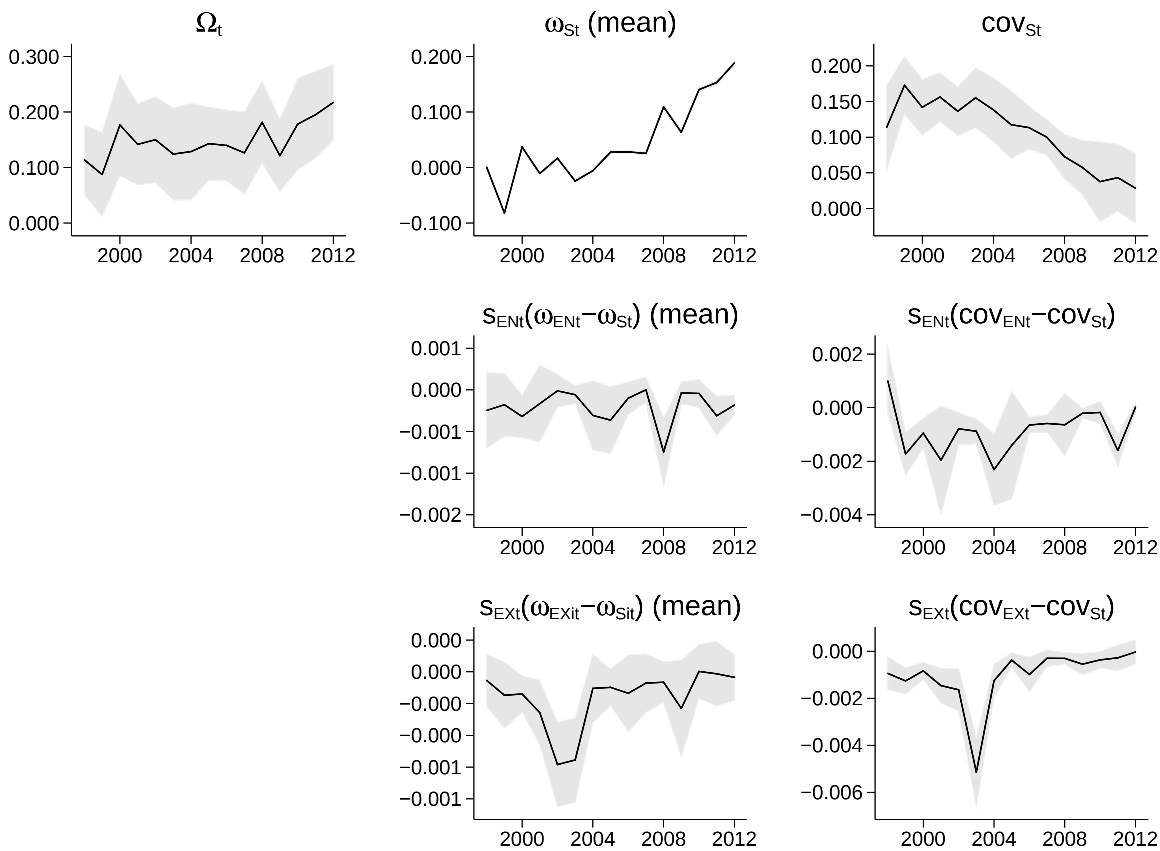
Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all firms in the respective industry. $\bar{\hat{\theta}}^k_{it}$, $\bar{\hat{\theta}}^l_{it}$ and $\bar{\hat{\theta}}^m_{it}$ are averages of the estimated output elasticities of capital, labour and material respectively. $R\bar{\hat{T}}S_{it}$ is the average of the estimated RTS. $Ma\bar{\hat{r}}kup_t$ is the average of the estimated annual markups. The lower panel gives the average, of the estimated in equation (2.2), effects on future TFP from exporting, importing and two-way trading. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

Figure 2.A.1: Aggregate productivity growth.



Notes: Authors' calculations. This is the first year difference of Ω_t. Ω_t is the share weighted average of TFP with deflated nominal sales as weights. TFP is computed from a production function estimated under IC at the industry level ($Nace$).

Figure 2.A.2: OP decomposition with entry and exit.



Notes: Authors' calculations. Ω_t is the share weighted average of TFP with deflated nominal sales as weights and is the sum of all of the components in the second and third columns. TFP is computed from a production function estimated under IC at the industry level ($Nace$). The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval, for each point estimate of the OP decomposition, following the procedure of HIM.

Appendix 2.B Data for EU

We construct a firm-level panel of manufacturing firms for 18 EU countries over the period 2002 to 2012. The data source is the Amadeus database by Bureau van Dijk Electronic Publishing (2011) (BvDEP). BvDEP regularly updates the information set in Amadeus and releases a monthly DVD containing the latest information on ownership. Firms that exit the market are dropped fairly rapidly. We use a time series of (annual) DVDs to construct a consistent database that comprises a complete set of financial information over time. This allows us to build a dataset with nearly full financial and administrative information, i.e. balance sheet, profit and loss account activities, location, exit and entry. Merlevede et al. (2015) describe the construction and representativeness of the data at length.

We focus on the sample of active manufacturing firms that file unconsolidated accounts. We retain firms reporting sales, tangible fixed assets, number of employees, material costs and NACE Rev.2 2-digit industry classification. We remove outliers using the BACON method, as described in the main body of the paper. This results in an unbalanced panel of 2157986 observations for the period 2002-2012 (see Table 2.B.1).

Table 2.B.1: Summary Statistics

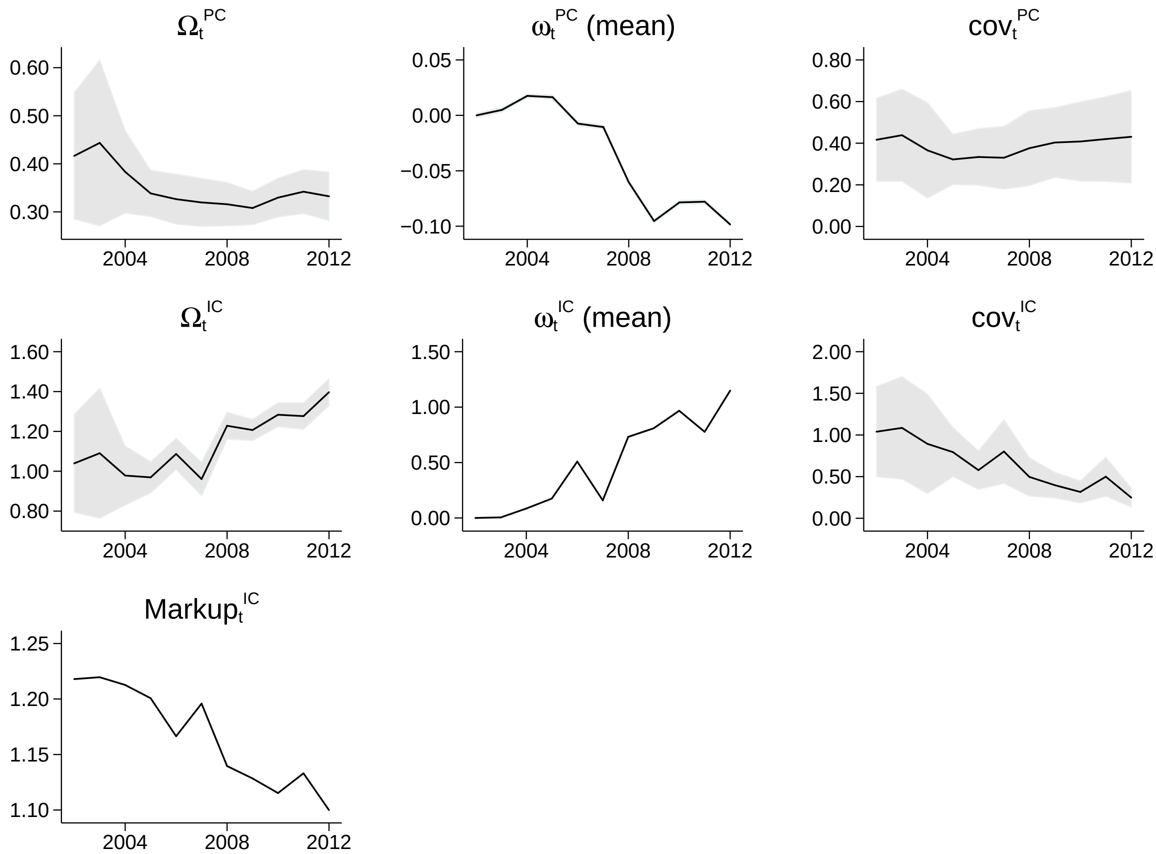
	Obs.	Mean	St.Dev.	p25	p50	p75
$Sales^a$	2157986	27880	587060	357	1188	5002
$Tangible\ fixed\ assets^a$	2157986	7305	156500	38	175	922
$Material\ costs^a$	2157986	18255	425734	126	515	2533
$Employment$	2157986	42	278	4	10	27
$Surviving$	2157986	.78	.41	1	1	1
$Entering^b$	2157986	.14	.35	0	0	0
$Exiting$	2157986	.077	.27	0	0	0
$Experimenting$	2157986	.015	.12	0	0	0

Notes: [a] monetary variables in thousand Euro, [b] includes Experimenting firms. BvDEP database for manufacturing firms in 18 EU countries for the period 2002 to 2012.

Monetary variables are deflated using the appropriate NACE Rev.2 2-digit deflator. All deflators are constructed following the approach describe in the main body of the text. Real output Y is sales deflated with producer price indices. Capital K is tangible fixed assets deflated with the capital deflator, and real material inputs M is material inputs deflated by an intermediate input deflator. Labour L is the number of employees.

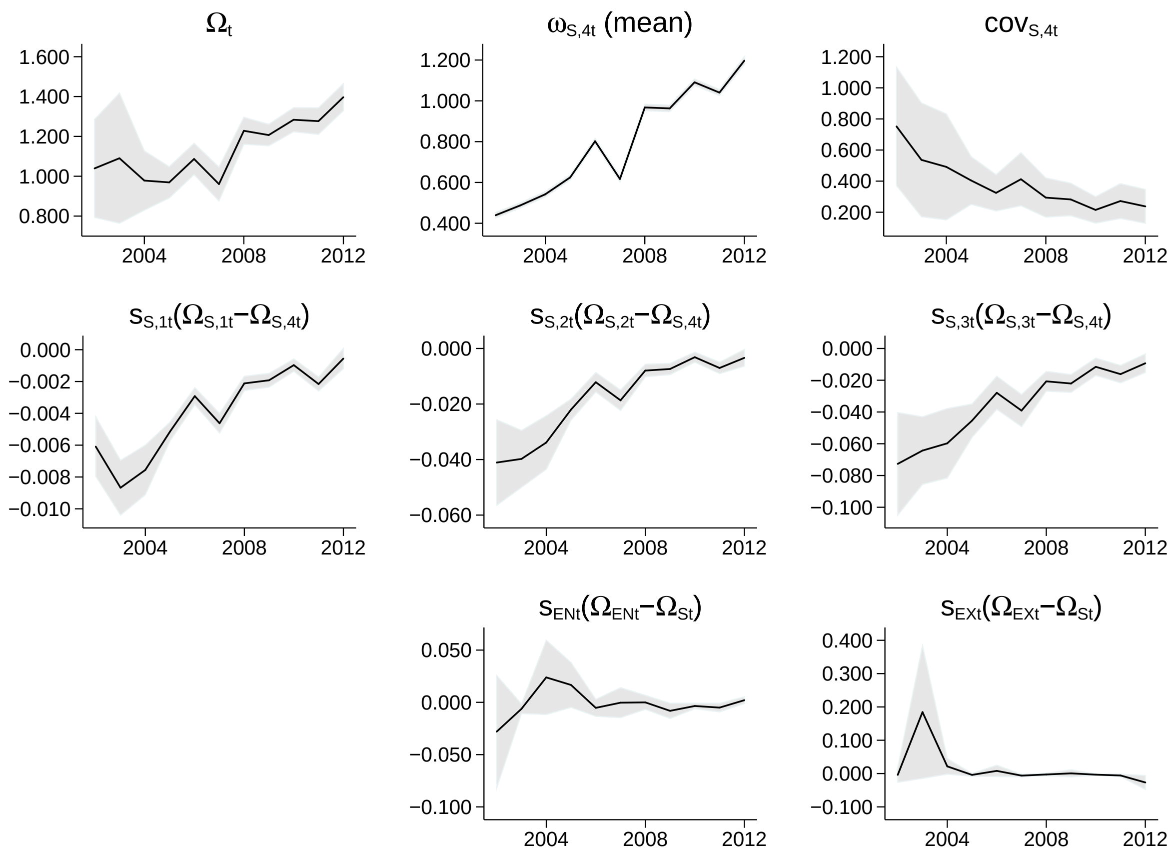
Appendix 2.C Additional Figures and Tables for EU

Figure 2.C.1: Aggregate productivity, OP decomposition and markup in EU



Notes: Authors' calculations. Ω_t is the share weighted average of TFP with deflated nominal sales as weights and is the sum of the components in the second and third columns. All TFP measures are based on production functions estimated at the industry level ($Nace$) pooling all EU countries together. The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval, for each point estimate of the OP decomposition, following the procedure of HIM. Markup contains the average across industries of estimated markups in each year.

Figure 2.C.2: OP decomposition with entry, exit and size in EU



Notes: Authors' calculations. Ω_t is the share weighted average of TFP with deflated nominal sales as weights and is the sum of all other components in the panel. TFP is computed from a production function estimated under IC at the industry level ($Nace$) pooling all EU countries together. The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval, for each point estimate of the OP decomposition, following the procedure of HIM.

3

Productivity Effects from Inter-industry Offshoring and Inshoring: Evidence from Belgium*

3.1 Introduction

A large literature has examined the effect of export or import behaviour on future productivity, known as "learning by exporting" or "learning by importing" (De Loecker, 2007; Vogel and Wagner, 2010; De Loecker, 2013; Manjón et al., 2013). On the one hand, product innovation, upgrading of production processes, improvements of technical standards, managerial practices, and inventory techniques have all been suggested as possible mechanisms for export-driven productivity improvements (Clerides et al., 1998; Fernandes, 2007; Lileeva and Trefler, 2010; Kasahara and Lapham, 2013; Manjón et al.,

*This chapter is submitted to the Canadian Journal of Economics and is based on a paper co-authored with Bruno Merlevede. We thank participants at the U4-Workshop Oct. 2014, SMYE May 2015, Ecores Summer School May 2015, ETSG Sept. 2015, ITSG Dec. 2015, Ghent University Internal Seminar Oct. 2015, 8th FIW Dec. 2015, FREIT Jun. 2016, CIE Jun. 2016, and GTD Jun. 2016 for their comments and suggestions. Special thanks are extended to Andrea Ariu, Sotiris Blanas, Douglas L. Campbell, Davide Castellani, Ruben Dewitte, Gerdie Everaert, Rebecca Freeman, Dirk Van de gaer, Joep Konings, Kun Li, Inmaculada Martínez-Zarzoso, Klaas Mulier, Gianmarco Ottaviano, Glenn Rayp, David A. Rivers, Mark J. Roberts, Ilse Ruyssen, Johannes Schmieder and Samuel Standaert.

2013). On the other hand, various potential channels through which the import of intermediate inputs affects future productivity include: knowledge transfer via intermediate inputs; access to more varieties (of potentially higher quality); complementarity with domestic inputs; and cost saving from process and product innovation (Markusen, 1989; Grossman and Helpman, 1991; Antràs et al., 2014; Bas and Strauss-Kahn, 2015; Halpern et al., 2015).

Increased opportunities for international trade, generated by decreases in trade and communication costs, have resulted in the fragmentation of production within and across national boundaries (Antràs et al., 2012). While there is a substantial amount of research that examines the productivity effects of firms' or industries' offshoring behaviour[1] (e.g. Amiti and Wei, 2005; Amiti and Konings, 2007; Tomiura, 2007; Halpern et al., 2015), potential productivity effects of offshoring along the domestic supply chain have received less attention. Blalock and Veloso (2007) focus on increased competition for suppliers of domestic intermediate goods through offshoring by their clients. They find evidence that vertical supply chain relationships serve as a channel through which indirect import-driven productivity upgrading occurs in Indonesia.

In this paper we generalise their analysis and further examine potential productivity effects for a given firm stemming from the fact that its suppliers also serve export markets with intermediate goods. Mirroring offshoring, we define 'inshoring' as exports of intermediate goods to both affiliated and unaffiliated foreign firms.[2] To the extent that this increases the quality and range of the set of domestically available intermediate inputs, a given local client may benefit in terms of positive productivity effects. To cover all possible channels, we also examine whether sourcing from local suppliers that offshore or supplying local clients that inshore are associated with pass-on productivity effects for a given firm.

As such, our analysis deals with potential productivity effects to a given firm associated with the internationalisation behaviour of its local clients and suppliers. Since firms are more likely to share new knowledge with related parties along the supply chain than with

[1] Our notion of offshoring includes both international outsourcing and also production transfers within MNCs. See Crinò (2009) for an overview of definitions.

[2] The term was initially inspired by Slaughter (2004) who used "insourcing" to refer to subsidiaries of foreign-headquartered multinationals, while Liu and Trefler (2008) coined the term as the flip side of offshore outsourcing, i.e. the sale of services to unaffiliated foreign firms.

competitors (Blalock and Veloso, 2007), we focus on the inter-industry productivity effects of offshoring and inshoring. Local firms may then experience indirect productivity effects of internationalisation through participation in the domestic supply chain.

The mechanisms we have in mind bear close resemblance to vertical productivity effects from foreign direct investment (FDI) as in Javorcik (2004b) and Blalock and Gertler (2008). However, in our case, the conduit is not FDI. Rather, it is offshoring and inshoring by vertically related firms. On the one hand, firms potentially learn from performing tasks (Arrow, 1962; Stokey, 1988; Parente, 1994; Jovanovic and Nyarko, 1996) required when exchanging intermediate inputs with upstream and downstream sectors that also inshore or offshore. Such tasks entail organisational restructuring, network sharing, technical and managerial challenges, knowledge transfers, and indirect competition pressures that force firms to innovate or upgrade quality and cost savings. Additionally, learning might be relationship-specific when production requires coordination of inputs from multiple firms (Kellogg, 2011). This includes both knowledge accumulation and personal interaction between producers and providers of intermediate-input that work together in a contracting relationship. Empirically, we therefore model potential productivity effects from inter-industry offshoring and inshoring as a learning process in the production function and allow past experience from inter-industry offshoring and inshoring to affect future productivity.

As in most empirical international trade research, productivity measurement is a core element in our analysis. Recent literature typically relies on proxy variable methods which aim to correct for endogeneity bias that arises when firms choose inputs while knowing their productivity level (e.g. Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2006). Despite their popularity and prevalence, proxy variable methods suffer from identification issues when the production function contains at least one flexible input such as materials (Gandhi et al., 2016). As such, there is not enough variation outside the production function system to identify the flexible input. To circumvent this problem, applied economists focus on value-added production functions, i.e. they subtract materials from output. As a result, productivity estimates suffer from a 'value-added bias' that overstates their dispersion and heterogeneity. Intuitively, one erroneously attributes the variation of material input to productivity. To correct for this, we use the estimator for gross-output production functions with at least one flexible input proposed by Gandhi, Navarro, and Rivers (2016) (henceforth GNR). Their approach controls for both the endogeneity and value-added bias. Further, we point to a common specification bias in applied work when ignoring the dynamic nature of productivity.

We consider a small open economy to analyse productivity effects along the supply chain driven by trade in intermediates in linked industries. We combine firm level data for Belgian manufacturing firms for the period 1995-2011 with input-output tables (IO-tables). The latter are used to construct industry-level measures of inter-industry offshoring and inshoring intensities based on a measure proposed by Merlevede and Michel (2013).

The following findings emerge. We confirm important biases arising from ignoring the dynamic nature of productivity and specifying a value-added rather than a gross-output production function. Export of intermediates by a given firm's local suppliers, i.e. upstream inshoring, is the only robust channel of inter-industry productivity effects. Sourcing from industries that also export these intermediates seem to be associated with higher productivity levels of a given firm. This effect likely originates from access to better intermediates that are also exported. On the basis of our preferred point estimate, a one standard deviation increase in upstream inshoring is associated with a productivity increase of 0.45% in the short run and 8.73% in the long run. In support of our result we find these effects to be stronger for those firms and industries that are less likely to be directly internationally involved. Finally, we do not find such effects if the destination of the exported intermediates is China or Eastern Europe.

The remainder of this paper is organised as follows. In Section 3.2 we discuss inter-industry offshoring and inshoring and define how the relevant proxies are constructed. In Section 3.3, we describe the empirical methodology with a focus on the aforementioned biases and in Section 3.4 we describe the data. Section 3.5 presents results, including an analysis of potential biases and an exploration of heterogeneity of various forms. Finally, Section 3.6 offers some concluding remarks.

3.2 Defining Inter-industry Offshoring and Inshoring

To measure inter-industry offshoring and inshoring activities, we construct proxies at the industry-year level using supply-use and IO-tables from the World Input-Output Database (WIOD) (*cf. infra*). For downstream offshoring, we build on a measure introduced by Merlevede and Michel (2013) and construct similar measures for upstream offshoring and downstream/upstream inshoring. For a detailed derivation we refer the reader to appendix 3.A and limit ourselves to a shorter description here. The measure to capture downstream offshoring is the following:

$$OFF\_down_{jt} = \sum_{d \neq j} \theta_{jdt} \Phi_{jdt} \tag{3.1}$$

where θ_{jdt} is the proportion of industry j's domestic supply sold to downstream industry d in time t. Φ_{jdt} is constructed as a weighted sum of offshoring intensities in industry d of products that industry j supplies to downstream industry d in time t. Weights are defined as the relative importance of each product in the output mix of products by j. This approach departs from simple industry averages and fully exploits information about products exchanged between industry pairs available in supply-use tables. It captures secondary output and allows for a more precise identification of linkages between industries. Φ_{jdt} measures the offshoring behaviour of downstream industry d that affects (firms in) industry j. We obtain a value of Φ for all possible industry pairs involving the focal industry j and use θ_{jdt} to generate a single value for OFF_down_{jt} as a weighted average of Φs. The weights used are the shares of industry j's output supplied to downstream industries d at time t taken from the domestic IO-table.[3]

Downstream offshoring captures downstream demand side shocks or import competition. Firms compete internationally to horizontally supply differentiated intermediate inputs to downstream industries. To survive and remain competitive, these firms need to reduce costs and improve productivity. Should the intermediates be complements to those offshored by downstream firms, productivity effects may result from upgrading production processes in order to match specificities and quality standards of the complementary intermediate inputs used in the production process of downstream firms (see Blalock and Veloso, 2007).

In a similar spirit, we define 'upstream inshoring' for a focal firm as sourcing intermediates from (a firm in) an industry that also exports these intermediate goods to both affiliated and unaffiliated firms in foreign countries. For instance, think of a firm in the Manufacture of Computer and Related Services industry that supplies intermediate inputs

[3]Since they refer to domestic supply only, θ_{jdt} will be affected by offshoring decisions of firms in downstream industries d. We therefore fix each θ_{jd} to its value at 1995, the start year of the sample.

to a firm in the Manufacture of Office Machinery and Computers industry. When the former also exports these products for intermediate use abroad, i.e. inshores, this may affect the productivity of the firm in the Manufacture of Computer and Related Services industry. Productivity effects then may result from the availability of higher quality domestic inputs. However, potential productivity effects need not be limited to direct ones. They may extend to more indirect effects such as diffusion of management practices, benefits from international networking and organisational restructuring. To analyse such potential effects we define IN_up_{jt} as:

$$IN\_up_{jt} = \sum_{u \neq j} \zeta_{jut} \Psi_{jut} \tag{3.2}$$

where Ψ_{jut} measures the inshoring activity of upstream industry u with respect to products that industry j uses as intermediate inputs. More precisely, we obtain product specific inshoring intensities by industry u and then combine them with the shares of these products in industry j's input mix to generate a weighted average. Next, we average over partner industries u using ζ_{jut}, defined as the proportion of industry j's domestically sourced intermediate inputs from upstream industries u at time t, to obtain IN_up_{jt}.

In addition to downstream offshoring and upstream inshoring that are based on the direct exchange of 'common' products, we analyse further forms of indirect internationalisation through domestic supply chain participation. This includes potential productivity effects from upstream offshoring and downstream inshoring, where no product-specific links are at play. However, offshoring in a previous stage or inshoring in a subsequent stage of the supply chain may also result in indirect productivity spillover effects similar to those described above. To analyse such inter-industry effects we define measures for upstream offshoring and downstream inshoring as follows:

$$OFF\_up_{jt} = \sum_{u \neq j} \zeta_{jut} \Omega_{jut} \tag{3.3}$$

where ζ_{jut} is again the proportion of industry j's intermediate inputs sourced from upstream industries u at time t. Ω_{jut} is the offshoring intensity in industry u, averaged over all products since in this case there is no direct product link between industries j

and u.

$$IN\_down_{jt} = \sum_{d \neq j} \theta_{jdt} \Theta_{jdt} \tag{3.4}$$

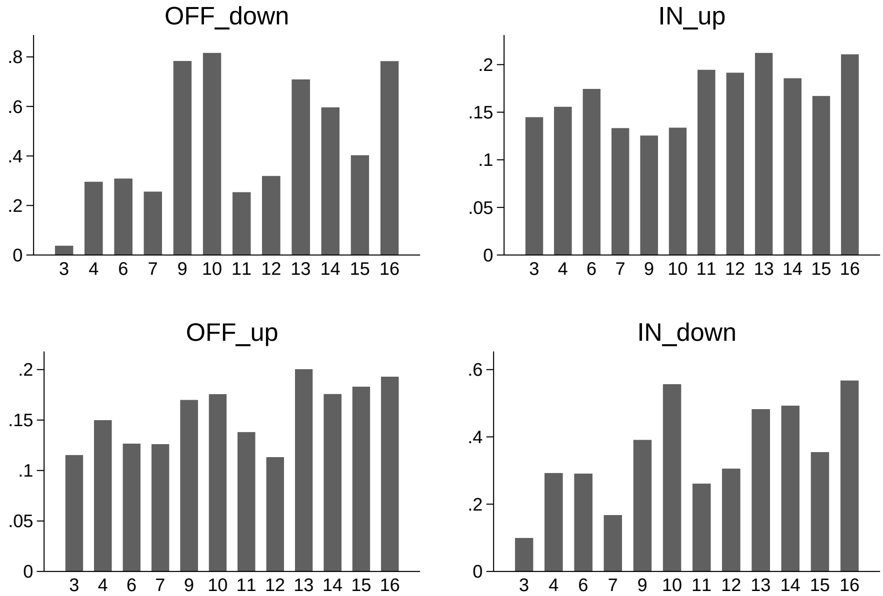
where Θ_{jdt} measures the inshoring intensities of downstream industries d and θ_{jdt} is defined as above. Upstream offshoring is a supply side effect originating from the import of intermediate inputs by the focal firm's suppliers. In this case, the learning mechanisms rely on knowledge diffusion from upstream to downstream industries (Grossman and Helpman, 1995; Coe and Helpman, 1995; Connolly, 2003). Downstream inshoring is a potential demand side effect that, on top of the aforementioned indirect effects, may result from the demand for increased quality of intermediate inputs from downstream industries.

Furthermore, in our empirical model we include intra-industry offshoring and inshoring intensities among the explanatory variables, but think of them as important control variables for two principal reasons. First, our firm-level data do not allow us to determine firm-specific offshoring and inshoring intensities and the industry-level intensities are an average over firms with and without internationalisation activities. Second, our measures in (3.1)-(3.4) poorly capture inter-industry effects and therefore exclude any intra-industry offshoring and inshoring activity. Given that the industry classification in the IO-tables is fairly aggregated, within-industry supply chain relations are likely to exist and will also be reflected in the industry-level offshoring and inshoring intensities. This makes the intra-industry variables important controls, but their interpretation is hampered by the fact that they reflect a net outcome of different mechanisms.

All four measures, OFF_down_{jt}, IN_up_{jt}, OFF_up_{jt}, and IN_down_{jt}, are inherently relative where firms with larger values are those in industries faced with relatively more downstream/upstream offshoring/inshoring. Figure 3.1 plots the mean values over time for all Belgian manufacturing industries for each of the inter-industry variables in (3.1)-(3.4). We observe a substantial variation across industries: industry 10, Manufacture of Rubber and Plastic Products, faces the highest values for downstream offshoring and inshoring; Industry 13, Manufacture of Machinery and Equipment, (together with industry 16, Other Manuafcturing) scores high on all four variables; Industry 3, Manufacture of Food, Beverages and Tobacco, is generally confronted with the lowest values for inter-industry internationalisation.

Figure 3.2 contains boxplots of the annual changes by industry for each of the variables.

Figure 3.1: Inter-industry offshoring and inshoring (mean over time by industry)



Source: Authors' calculations based on WIOD

The figure illustrates that for the case of Belgium we find no clear trend for the different measures for the different industries. The absence of any clear overall trends fits with Belgium's economic history as a small, heavily (intermediate) trade oriented, and deeply EU integrated economy. However, when we calculate the variables for China and Eastern Europe separately, we find considerable increases over the period considered for all of the variables (*cf. infra*). Table 3.1 in the data section contains further summary statistics.

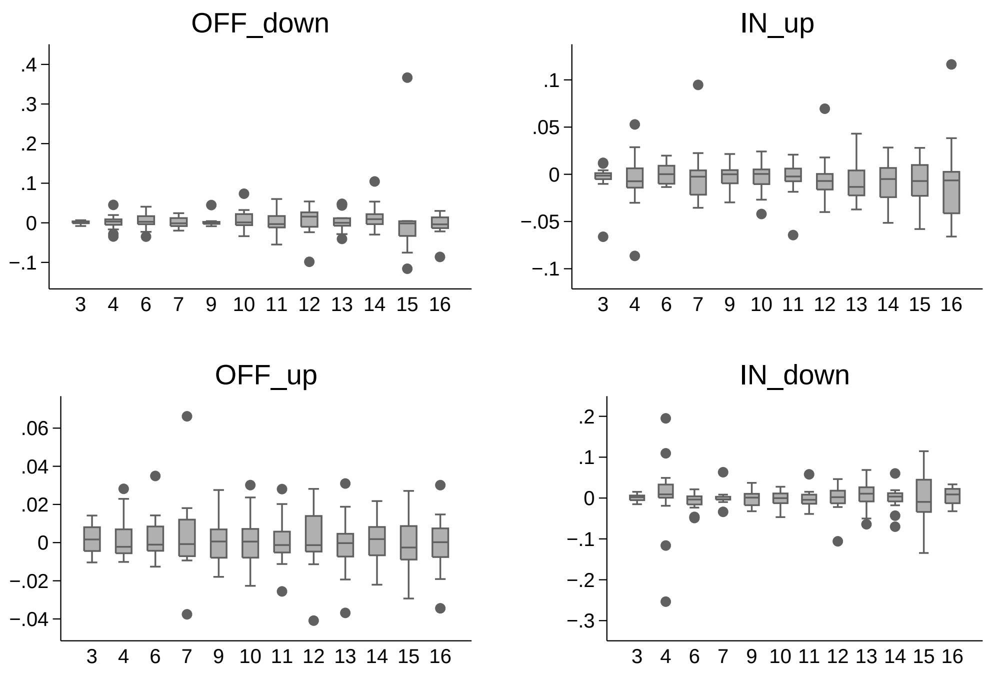
3.3 Empirical Methodology

3.3.1 Total Factor Productivity

To analyse potential productivity effects of inter-industry offshoring and inshoring, we consider a flexible gross-output production function $Y_{it} = F(K_{it}, L_{it}, M_{it})e^{\omega_{it}+\epsilon_{it}}$, with Hicks-neutral total factor productivity ω_{it} (TFP). In logs, the production function to be estimated is of the following form:

$$y_{it} = f(k_{it}, l_{it}, m_{it}) + \omega_{it} + \epsilon_{it} \tag{3.5}$$

Figure 3.2: Inter-industry offshoring and inshoring (annual differences by industry)



Source: Authors' calculations based on WIOD

where y_{it}, k_{it} and m_{it} are log values of deflated (at the industry level) sales, tangible fixed assets and material costs, respectively, and l_{it} is the log of the total number of employees of firm i at time t. ω_{it} is unobserved to the econometrician but known to the firm. Ex-post shocks, i.e. after the firm's decision on which inputs to use, are picked up by ϵ_{it}.[4]

The applied production function estimation literature has primarily employed structural approaches including both dynamic panel methods (Arellano and Bond, 1991; Blundell and Bond, 1998, 2000) and proxy variable methods (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2006). The main focus has been to solve for endogeneity, also known as 'simultaneity' or 'transmission bias.' Such bias originates from the fact that firms know their productivity level when they decide on which inputs to use (Marschak and Andrews, 1944; Griliches and Mairesse, 1999).

Despite their popularity and prevalence, proxy variable methods suffer from identification issues when the production function contains at least one flexible input such as materials. These issues have been highlighted by Mendershausen (1938); Marschak and

[4]Given that y_{it} is an observable variable in our dataset, we expect ϵ_{it} to also contain measurement error to output and prices. This is assumed to be symmetric across firms within each industry and therefore does not affect our estimation.

Andrews (1944); Bond and Söderbom (2005); Ackerberg et al. (2006) and formalised by GNR. Intuitively, there is not enough variation outside the production function system to identify the flexible input.[5]

To circumvent this problem, applied economists have focused on value-added production functions where the flexible input, materials, is subtracted from output and thus 'disappears' from the production function. Such a specification, however, will fail to identify the true variable of interest, i.e. TFP, even under very strong assumptions (Bruno, 1978; Diewert, 1978; Basu and Fernald, 1997). Estimates suffer from a value-added bias causing the dispersion and heterogeneity in TFP to be overstated. Intuitively, one erroneously attributes the variation of material inputs to productivity and resultantly ends up with a distorted image of the productivity distribution and consequently misleading policy implications (*cf*. Section 3.5.1).

GNR propose a simple estimator for gross-output production functions with at least one flexible input. They establish identification by exploiting information in the first order condition with respect to the flexible input from the firm's static profit maximisation problem. This flexible approach controls for both the transmission and value-added bias. It imposes no specific functional form, nor does it rely on strong assumptions imposed in alternative proxy variable frameworks, e.g. the assumption of scalar unobservability to invert the proxy demand function (e.g. Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2006). In line with most of the the proxy variable methods, the GNR procedure follows two-steps and allows us to both estimate production functions and identify the productivity effects from inter-industry offshoring and inshoring. Appendix 3.B outlines the assumptions and steps followed.

Note that TFP is not identical to disembodied technological change, often referred to as the 'Solow Residual' (Solow, 1957). Here TFP also includes the impact of inputs that are not explicitly measured (e.g. management and human capital skills). Further, note that our TFP estimates are revenue based as we do not observe physical output, but only monetary values which we deflate at the industry level. Results should be interpreted

[5]Firm specific prices, to the extent that they are exogenous, can potentially serve as instruments for flexible inputs and solve for the identification problem (Doraszelski and Jaumandreu, 2013). However, in practice it is hard to find prices at the firm/plant level that reflect differences in expected rather than chosen prices (Griliches and Mairesse, 1999; Ackerberg et al., 2007). Therefore, in most datasets, prices will capture market power and input/output quality differences rendering them endogenous (Fox and Smeets, 2011; Kugler and Verhoogen, 2012; Atalay, 2014).

bearing this caveat in mind (Klette and Griliches, 1996).

3.3.2 Effects of Inter-industry Offshoring and Inshoring on TFP

We now specify how we model the effects of inter-industry offshoring and inshoring on productivity as a learning process. We start with the two-stage specification that is typical to the literature and argue why it is misspecified. We then present the correctly specified one-stage procedure on which inference will be based.

To analyse the inter-industry productivity effects of offshoring and inshoring we allow the relevant measures to shift the future productivity path, ω_{it}. Typically, a two-stage approach would be taken for such a problem. In a first stage, a TFP estimate would be obtained using one of the techniques discussed above, to be followed by a second stage where TFP as a dependent variable is related to the variables of interest. A non-negligible part of the empirical literature employs a static specification (henceforth 2S-Static) in the second stage, which in our case looks like:

$$\hat{\omega}_{it} = \gamma_c + \gamma_p proxies_{jt-1} + \gamma_x X_{it-1} + \alpha_t + \alpha_j + \alpha_r + \xi_{it} \tag{3.6}$$

where $proxies_{jt-1}$ is the vector of inter- and intra-industry offshoring and inshoring proxies, at the industry-level (j); X_{it-1} is a vector of dummies indicating whether a firm belongs to a multinational (MNC), is owned by a Belgian firm (SHH_BE), or owns another Belgian firm (SUB_BE); and α_t, α_j and α_r are a set of dummies for time, industry and region fixed effects, respectively.

When using specification (3.6) in the second stage, a conceptual gap with stage one emerges (Fernandes, 2007). Stage one assumes a Markov process for productivity, while stage two uses a static specification for productivity. Stage two thus ignores the dynamic nature of productivity which results in serial correlation that can not be eliminated with fixed effects. As such, equation (3.6) is misspecified. The following dynamic specification (henceforth 2S-Dynamic) resolves this issue:

$$\hat{\omega}_{it} = \gamma_c + \rho\hat{\omega}_{it-1} + \gamma_p proxies_{jt-1} + \gamma_x X_{it-1} + \alpha_t + \alpha_j + \alpha_r + \xi_{it} \tag{3.7}$$

Pooling all manufacturing industries (and firms), the above equation can consistently be estimated since the number of industries and regions is small compared to the panel dimension.[6]

However, the two-stage approach suffers from a second conceptual problem. In equation (3.7) current productivity—conditional on lagged productivity—depends on the lagged proxies and other determinants that are in the firm's information set when decisions are made. These inter-industry effects (and other determinants that possibly shift the future productivity path) are not taken into account in the Markov process in the first-stage. To solve for this inconsistency, we introduce the relevant proxies and control variables in the law of motion and estimate them—as in Aw et al. (2008); Doraszelski and Jaumandreu (2013) and De Loecker (2013)—*within* the GNR procedure in (3.8).[7] Henceforth we refer to the estimation of (3.8) as 'One-Stage' (1S-Dynamic).[8]

$$y_{it} = f(k_{it}, l_{it}, m_{it}) + \Big(g(\omega_{it-1}, proxies_{jt-1}, X_{it-1}, \alpha_t, \alpha_j, \alpha_r) + \xi_{it}\Big) + \epsilon_{it} \tag{3.8}$$

Because proxies are industry-year specific, (3.8) is always estimated at a more aggregate level in order to maintain sufficient variation. Therefore, we use time α_t, industry α_j and region α_r fixed effects to account for macroeconomic shocks and aggregate structural differences at the industry and region level. We use (3.8) to compare the recent GNR procedure to that of Ackerberg, Caves, and Frazer (2006) (henceforth ACF) which is widely popular. We explore the value-added bias by comparing our GNR estimates to those obtained when using the ACF method with a value-added production function as described in Appendix 3.C. What is more, gross-output production functions with at least one flexible input are non-parametrically non identified under any of the traditional dynamic and semi-parametric estimation methods. Intuitively, there is not enough variation outside the production function system to identify the flexible input. Therefore, we also compare

[6] In the case of firm fixed effects the latter estimation is inconsistent. To solve for the endogeneity induced by the correlation between the persistence term and the unobserved firm fixed effects, Fernandes (2007) and Topalova and Khandelwal (2011) apply an Arellano and Bond (1991) approach. But as noted by Blundell and Bond (1998), the latter performs poorly when $\hat{\omega}_{it}$ is close to a random walk. Therefore, a "System GMM" approach can be applied. This procedure also controls for measurement error introduced by the use of estimated lagged TFP in our specification. This is because lagged values of $\hat{\omega}_{it-1}$ are assumed to have measurement error not correlated with $\hat{\omega}_{it-1}$'s measurement error.

[7] A direct approach where the variables of interest are incorporated in the first-step's control function (e.g. Fernandes, 2007; Topalova and Khandelwal, 2011) is problematic since it ignores the dynamic nature of TFP and just provides an equilibrium relationship between TFP and the variables of interest, rather than a learning process framework which is pertinent to us. In practice, incorporation in the control function only helps to control for unobserved price changes induced from the relevant shocks.

[8] For comparability with the previous models we use a linear specification of $g(\cdot)$.

GNR with a gross-output production function using the ACF estimation procedure.[9] The latter estimation is computationally feasible, but it does not identify the true production function parameters.[10]

As opposed to ACF, the GNR framework allows to develop a specification that accounts for firm fixed effects.[11] GNR indicate that allowing for fixed effects does not bear an important effect on the estimated elasticities of the production function. However, as our main interest lies with the estimation of the impact of the proxies we do feel that it is important to control for firm fixed effects (α_i) in (3.8). Therefore, (3.9) will be our preferred specification (henceforth 1S-D-FFE).

$$y_{it} = f(k_{it}, l_{it}, m_{it}) + \Big(g(\omega_{it-1}, proxies_{jt-1}, X_{it-1}, \alpha_t, \alpha_i) + \xi_{it}\Big) + \epsilon_{it} \tag{3.9}$$

Endogeneity issues should be less of a concern given our focus on inter-industry effects where productivity shocks are transmitted through relevant linkages with firms in upstream or downstream industries. To further alleviate possible endogeneity concerns, we take the following additional steps.

First, a given firm might have some impact on the offshoring and inshoring choice of its client or supplier industries through affiliated firms in these industries. This would render our proxies endogenous for sufficiently granular firms. Therefore we construct two variables to indicate whether the focal firm owns any domestic subsidiaries (SUB_BE) or is owned by any other domestic firm (SHH_BE). Using the above variables and the MNC status of a firm, we control for any type of domestic demand or supply chain relationship between parent and affiliate firms.

Second, we assume that the activity of upstream or downstream firms is not immediately observed. It is gradually explored by the focal firm, resulting in a delay in the transmission of productivity effects. We use one year lagged proxies to capture such sluggishness. Because it is counter intuitive that current firm-level TFP would affect lagged values of inter-industry offshoring and inshoring, potential simultaneity bias is less of a concern. Intra-industry offshoring and inshoring are expected to contemporaneously affect firm productivity which is consistent with the timing assumption for material inputs used in

[9]The procedure follows from Appendix 3.C but with a gross-output translog production function.
[10]See Bond and Söderbom (2005) for an exposition under a Cobb-Douglass specification.
[11]See Appendix C of their paper.

estimating TFP. This is because material inputs are assumed to be flexible. In this case, the decision to offshore or inshore is endogenous and should be modelled accordingly.[12]

3.4 Data

We construct a firm-level panel of Belgian manufacturing firms from 1995 to 2011 from the Amadeus database by Bureau van Dijk Electronic Publishing (2011) (BvDEP). BvDEP regularly updates the information set in Amadeus and releases a monthly DVD containing the latest information on ownership. Firms that exit the market are dropped fairly rapidly. For a complete set of financial and ownership information over time, we use a time series of (annual) DVDs to construct a consistent database. This allows us to build a dataset with nearly full financial and administrative information, i.e. balance sheet, profit and loss account, activities, location, ownership, exit and entry. Merlevede et al. (2015) describe the construction and representativeness of the data at length.

We focus on the sample of active manufacturing[13] firms that file unconsolidated accounts.[14] We retain firms reporting sales, tangible fixed assets, number of employees, cost of employees, material costs, NACE 2-digit industry classification, NUTS region classification and ownership information. We remove outliers using the BACON method proposed by Billor et al. (2000).[15] Firms with less than two years of data are removed from the sample. The Manufacture of Leather, Leather and Footwear and the Manufacture of Coke, Refined Petroleum and Nuclear Fuel Products are removed due to an insufficient number of observations. This results in an unbalanced panel of 3117 firms and 33842 observations for the period 1995-2011 (see Table 3.1).

Monetary variables are deflated using the appropriate NACE 2-digit output deflator from the EU KLEMS database. Real output (Y) is sales deflated with producer price indices. Capital (K) is tangible fixed assets deflated by the average of the deflators of various NACE 2-digit industries (Javorcik, 2004b).[16] Real material inputs (M) is material

[12]See Amiti and Wei (2005); Görg et al. (2008); Ito and Tanaka (2012); Michel and Rycx (2014) and Halpern et al. (2015).

[13]Table 3.D.1 in Appendix 3.D provides an overview of the NACE Rev.1.1 2-digit industries included.

[14]This refers to accounts not integrating the statements of possible controlled subsidiaries or branches of the concerned company.

[15]BACON stands for Block Adaptive Computationally efficient Outlier Nominators. It is a multiple outlier detection method. The variables considered in the method are log of output, labour, capital and material.

[16]Machinery and equipment (29); office machinery and computing (30); electrical machinery and

inputs deflated by an intermediate input deflator constructed as a weighted average of output deflators, where country-time-industry specific weights are based on intermediate input uses retrieved from IO-tables. Labour (L) is the number of employees. Finally, MNC, SHH^{BE} and SUB^{BE} are dummy variables indicating whether at least 10% of a firm's shares are owned by a single foreign firm, if a firm is owned by any other domestic firm and if a firm owns any domestic subsidiary, respectively.

Table 3.1: Summary Statistics

Firm-level	Obs.	Mean	St.Dev.	p25	p50	p75
$Sales^*$	33842	44396	145387	7541	13734	30575
$TangibleFixedAssets^*$	33842	6077	23468	647	1685	4296
$MaterialCosts^*$	33842	26355	96143	3678	7378	17256
$Employees$	33842	135	361	31	55	116
MNC	33842	.13	.33	0	0	0
SHH^{BE}	33842	.37	.48	0	0	1
SUB^{BE}	33842	.24	.43	0	0	0
$\hat{\omega}_{GNR}$	33842	26	.16	26	26	26
$\hat{\omega}_{ACFVA}$	33662	16	.33	16	16	16
$\hat{\omega}_{ACFGO}$	33662	12	.08	11	12	12
Industry-level						
OFF_down	204	0.463	0.256	0.271	0.342	0.727
IN_up	204	0.169	0.051	0.130	0.165	0.202
OFF_up	204	0.155	0.034	0.128	0.155	0.183
IN_down	204	0.354	0.149	0.240	0.353	0.488

Notes: * Monetary variables in thousands of Euro. 3117 Belgian manufacturing firms and 12 industries over 1995-2011.

For the measurement of proxies we use the WIOD, which provides a time-series (1995-2011) of IO-tables for 40 countries worldwide and a table covering the rest of the world.[17] WIOD also contains industry-product supply and use tables that allow us to consider product-specific relationships between industries. The WIOD classification (CPA) contains 35 industries and 59 products.[18] A major advantage over other databases is that the WIOD varies over time and that information on imports of goods does not rely on the standard proportionality assumption. Instead, a more flexible approach is followed whereby import proportions vary over end-use categories. This provides greater variability over time and intermediate input types. This extra level of detail is expected to unmask

apparatus (31); motor vehicles, trailers, and semi-trailers (34); and other transport equipment (35).

[17]See Dietzenbacher et al. (2013) for a detailed description of the construction of the tables.

[18]See Table 3.D.1 in Appendix 3.D for correspondence with NACE Rev.1.1 2-digit.

possible heterogeneity and provide better identification.

Table 3.1 shows summary statistics for the firm and industry-level variables in our sample.

3.5 Results

In this section we first assess the importance of misspecification biases that are frequent in the literature and the impact of value-added bias on the estimated productivity effects of inter-industry offshoring and inshoring. We then analyse the productivity effects of inter-industry offshoring and inshoring in detail.

Table 3.2: TFP effects from inter-industry offshoring and inshoring.

	(1)	(2)	(3)	(4)	(5)
	GNR Gross-output			ACF Value-added	ACF Gross-output
	2S-Static	2S-Dynamic	1S-Dynamic	1S-Dynamic	1S-Dynamic
ω_{it-1}		0.942***	0.937***	0.927***	0.856***
		(0.006)	(0.004)	(0.011)	(0.020)
OFF_down_{jt-1}	-0.034	-0.039***	-0.043**	-0.070**	-0.011
	(0.047)	(0.012)	(0.019)	(0.035)	(0.015)
IN_up_{jt-1}	0.112**	0.103***	0.138***	0.026	-0.011
	(0.053)	(0.020)	(0.022)	(0.043)	(0.013)
OFF_up_{jt-1}	-1.456***	-0.345***	-0.407***	-0.056	0.008
	(0.132)	(0.051)	(0.051)	(0.150)	(0.041)
IN_down_{jt-1}	0.332***	0.076***	0.076***	-0.058	-0.007
	(0.034)	(0.012)	(0.014)	(0.048)	(0.024)
OFF_{jt-1}	0.034	0.074***	0.066***	-0.003	-0.009
	(0.052)	(0.012)	(0.019)	(0.055)	(0.016)
IN_{jt-1}	0.127**	0.063***	0.061***	-0.021	-0.006
	(0.056)	(0.014)	(0.020)	(0.036)	(0.011)
SHH^{BE}_{it-1}	-0.002	-0.000	-0.000	-0.000	-0.001
	(0.005)	(0.001)	(0.001)	(0.002)	(0.001)
SUB^{BE}_{it-1}	0.018**	0.000	0.000	-0.006	-0.001
	(0.007)	(0.001)	(0.001)	(0.004)	(0.001)
MNC_{it-1}	0.025***	0.003***	0.003*	0.011***	0.004***
	(0.008)	(0.001)	(0.002)	(0.003)	(0.001)
Observations	33842	33842	30725	30600	30600

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include additive year, industry and region fixed effects. In columns 1 and 2 standard errors are block-bootstrapped with 500 replications over the two-stage estimation procedure (with GNR two-step estimation procedure in the first stage) and are reported in parentheses below point estimates. In columns 3, 4 and 5 standard errors are block-bootstrapped with 500 replications over the GNR gross-output, the ACF value-added and the ACF gross-output estimation procedures, respectively, and are reported in parentheses below point estimates.

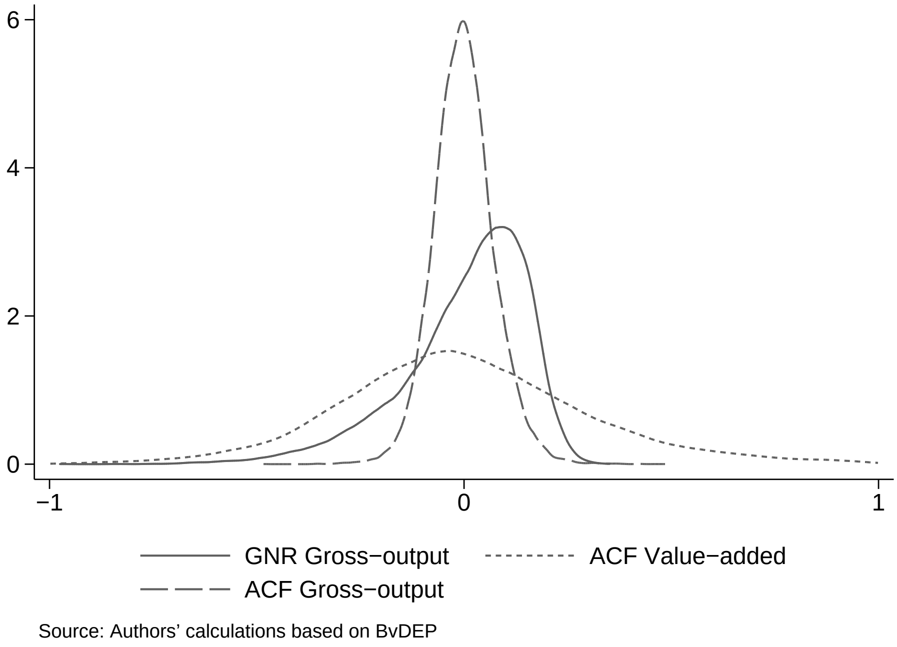
3.5.1 Misspecification and Value-added Bias

Misspecification. Notwithstanding that it is misspecified, we start with the static specification (3.6) because of its frequent use in the empirical literature. In Table 3.2, one immediately notices that the magnitude and significance of the coefficients in the first column (2S-Static) are not entirely consistent with those in the third column (1S-Dynamic) based on specification (3.8), leading to distorted inference. Therefore, it is crucial to at least control for the dynamic nature of productivity. Results using specification (3.7) in the second column (2S-Dynamic) control for the bias generated by ignoring the dynamic nature of productivity. Comparing columns 2 and 3 we do not observe large differences in estimated coefficients. Recall, however, that specification (3.7) still does not correctly specify the learning process.

Value-added Bias. To explore the effect of the value-added bias, we estimate productivity using the ACF two-step procedure with a value-added production function. In Figure 3.3, we plot the re-centered distributions of the estimated TFPs using the GNR gross-output and the ACF value-added. From a visual inspection we may conclude that the latter generates a more heterogeneous and dispersed distribution of TFP estimates. This indicates that the value-added bias can lead to seriously distorted estimates. In column 4 of Table 3.2 we therefore re-estimate column 3 based on the ACF estimation procedure under a value-added production function. It is clear from column 4 that the correctly specified one-stage procedure fails to produce any significant results for ACF value-added. Furthermore, point estimates are hardly comparable to those in column 3. This is likely driven by the presence of value-added bias.

ACF Gross-output. GNR prove that gross-output production functions with at least one flexible input are non-parametrically non identified under the ACF estimation method. We now proceed as if we are not aware of this result and erroneously estimate a gross-output production function using the ACF framework. Recall that the estimation is computationally feasible, but results in estimates of ω_{it} that do not represent TFP. As shown in Figure 3.3, the TFP distribution using ACF gross-output is more similar to that under the GNR procedure. It seems that the value-added bias is 'controlled for' when employing a gross-output specification. In column 5 of Table 3.2 we re-estimate the specification from column 3 but now use the ACF estimation procedure under a

Figure 3.3: Re-centered distribution of $\hat{\omega}_{it}$



gross-output production function. As can be seen from Table 3.2 the correctly specified one-stage procedure in column 5 produces results that are more in line with ACF under a value-added production function than with GNR. There are no significant effects on the variables of interest.

The findings in Table 3.2 emphasise the importance of correctly identifying gross-output production functions, as these identification issues potentially severely distort empirical results.

3.5.2 TFP Effects from Inter-industry Offshoring and Inshoring

In Table 3.3 we first introduce our preferred specification (3.9) and then test the robustness of our findings for a number of alternative assumptions in the estimation procedure (columns 2-4), the construction of the variables (columns 5-6), and the size of focal firms (columns 7-8).

Firm Fixed Effects. Column 1 shows the results of estimating (3.9) using the GNR procedure. The obtained point estimates are fairly similar to those from column 3 in Table 3.2. In terms of statistical significance we observe more substantial differences. When accounting for firm-specific effects, only upstream inshoring remains significant at the 1%-level, while upstream offshoring becomes significant only at the 5%-level, and downstream offshoring and inshoring lose all significance. Considering all of the evidence from Table 3.3 (and Table 3.4), upstream inshoring seems the only robust channel of inter-industry productivity effects. Supplying industries that also export these intermediates seem to be associated with higher productivity levels of the focal firm. This effect is likely to originate from access of the focal firm to better intermediates, since they are also exported. On the basis of the point estimate in column 1, a one standard deviation increase in upstream inshoring is associated with an increase in productivity of 0.45% in the short run and 8.73% in the long run.[19]

Table 3.3: The impact of inter-industry offshoring and inshoring using a one-stage dynamic firm fixed effects procedure under GNR and robustness to alternative assumptions

	(1) 1S-D-FFE	(2) Labour Timing	(3) Cobb Douglas	(4) Imperfect Competition	(5) Fixed in 2002	(6) Time Varying	(7) Size $L < 50$	(8) Size $L \geq 50$
OFF_down_{jt-1}	-0.039	-0.039	0.014	0.054	-0.020	-0.004	-0.038	-0.054
	(0.078)	(0.088)	(0.067)	(0.079)	(0.046)	(0.036)	(0.140)	(0.120)
IN_up_{jt-1}	0.133**	0.133*	0.241***	0.260***	0.133**	0.133***	0.211***	0.077
	(0.060)	(0.074)	(0.064)	(0.067)	(0.063)	(0.051)	(0.070)	(0.108)
OFF_up_{jt-1}	-0.334*	-0.334	-0.625***	-0.888***	-0.325*	-0.324**	-0.435	-0.256
	(0.186)	(0.214)	(0.184)	(0.151)	(0.185)	(0.152)	(0.305)	(0.327)
IN_down_{jt-1}	0.053	0.053	0.019	-0.052	0.055	0.055	0.051	0.064
	(0.061)	(0.054)	(0.048)	(0.040)	(0.058)	(0.062)	(0.044)	(0.101)
Observations	25463	25463	25463	25463	25463	25463	11016	14447

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include intra-industry offshoring and inshoring and dummies for multinational (MNC), domestic shareholder (SHH^{BE}) and domestic subsidiary (SUB^{BE}) presence. Standard errors are block-bootstrapped with 500 replications over the GNR two-step estimation procedure and are reported in parentheses below point estimates.

Alternative Assumptions. Although we prefer to allow for a flexible form of the production function we also test for a more restrictive one (Yatchew, 1998; Hulten, 2001, 2010, an issue raised by). Column 2 uses a Cobb-Douglas production function rather than the more flexible one underlying the result in column 1. Qualitatively, results are in line with column 1. Both upstream inshoring and offshoring are now significant at the 1%-level.

In column 3 we consider an alternative timing assumption for labour. We now assume

[19]The long-run effect is computed using estimates from column (1) of Table 3.3 based on the following formula: $IN\_up_{jt-1} * 1/(1-\rho) * sd(IN\_up_{jt}) * 100$, where IN_up_{jt-1} is the average short-run effect of upstream inshoring on future TFP as specified in equation (3.9), ρ is the average persistence of TFP, and $sd(IN\_up_{jt})$ is one standard deviation of the measure of upstream inshoring.

that rigidities in the Belgian labour market are so high that labour cannot adjust within the (accounting) year. This translates to an adjustment lag, resulting in a one period lag between the choice of labour and its realisation in the production process (hence in the accounting data). Therefore, labour, as in the case of capital, is predetermined in period t. To guarantee identification in the second step of the GNR procedure, we use l_{it} instead of l_{it-1} in the orthogonality conditions. Under such alternative timing assumptions, only upstream inshoring is significant at the 5%-level.

In column 4 we account for differences in prices in the output market in the estimation procedure. To control for unobserved variation in firm-specific prices we introduce more structure and assumptions (such as an iso-elastic demand system coupled with monopolistic competition similar to Klette and Griliches (1996) and De Loecker (2011)). For details about the estimation procedure we refer to GNR. By accounting for price differences in the output market, both the effects of upstream inshoring and offshoring turn out to be highly significant.

Construction of Variables. In columns 5 and 6 results are fairly robust to alternative treatment of the technical coefficients used to build the proxies. To test robustness we replace 1995 weights with 2002 fixed weights in column 4 and use time varying weights in column 5. Earlier findings are confirmed, with upstream inshoring reported as highly significant, and upstream offshoring also significant but less robust. Therefore our result does not seem to be driven by the choice of a specific weighting scheme. Notwithstanding this result, it is advisable to choose weights at the start or even before the start of the sample period for the reasons outlined above.

Firm Size. In columns 7 and 8 we split our sample into small (less than 50 employees) and large (50 employees or more) firms. On the one hand, we choose a cut-off of 50 since the large majority of Belgian firms have less than 250 employees. On the other hand, the 50 employee cut-off roughly splits the sample in two and comes with legal requirements in terms of union representation. This specific cut-off ensures that we observe both small and large firms in all industries considered.

We find that small firms are subject to upstream inshoring effects, but no other inter-industry effects. Larger firms do not seem to be affected by inter-industry offshoring and inshoring. This may reflect the fact that especially small firms are exposed to the effects of internationalisation through the domestic supply chain, whereas larger firms are generally more likely to already directly participate in global supply chains.

Our overall conclusion from Table 3.3 is that upstream inshoring, i.e. the effect of local suppliers also exporting these intermediates, is the only robust channel for inter-industry effects of offshoring and inshoring.

3.5.3 Heterogeneity

The result on firm size raises the question as to whether the effects of indirect internationalisation through domestic supply chain participation are specifically applicable to firms that do not or are less likely to directly participate in international or domestic supply chains. We test this in Table 3.4. For comparison reasons, the first column of Table 3.4 repeats column 1 from Table 3.3, our baseline result. The results in all other columns are also obtained from a 1-S-D-FFE estimation.

Table 3.4: TFP effects from inter-industry offshoring and inshoring

	(1) Full Sample	(2) MNC Links	(3) No MNC Links	(4) Relatively Upstream	(5) Relatively Downstream	(6) Upstream High-skill	(7) Upstream Low-skill
OFF_down_{jt-1}	-0.039	-0.043	-0.038	0.023	-0.052	-0.061	0.294
	(0.078)	(0.379)	(0.068)	(0.180)	(0.285)	(5.956)	(0.312)
IN_up_{jt-1}	0.133**	0.154	0.141**	0.187**	0.024	0.297	0.247**
	(0.060)	(0.513)	(0.060)	(0.086)	(0.331)	(1.420)	(0.118)
OFF_up_{jt-1}	-0.334*	-0.291	-0.345*	-0.287	-0.468	-0.685	0.029
	(0.186)	(1.529)	(0.182)	(0.330)	(1.102)	(5.497)	(0.766)
IN_down_{jt-1}	0.053	0.094	0.048	0.054	0.015	0.164	-0.060
	(0.061)	(0.270)	(0.052)	(0.074)	(0.271)	(0.637)	(0.138)
Observations	25463	3118	22345	13983	11480	3391	10592

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include intra-industry offshoring and inshoring, and dummies for multinational (MNC), domestic shareholder (SHH^{BE}) and domestic subsidiary (SUB^{BE}) presence. Standard errors are block-bootstrapped with 500 replications over the GNR two-step estimation procedure and are reported in parentheses below point estimates.

Local Supply Chain Participation. Purely domestic firms are less likely to be directly involved in an international supply chain than firms with foreign links. Therefore we may expect purely domestic firms to be more prone to inter-industry productivity effects. Column 2, reveals that in the specific subsample of firms that are either foreign-owned or own a foreign subsidiary, no significant effects can be detected from indirect participation in international supply chains. Foreign owned firms are likely to be directly involved in an international supply chain and their productivity (evolution) will be less prone to inter-industry offshoring effects. On the other hand, local standalone firms are more likely to depend on domestic clients and suppliers. For the sample of purely local firms, we find in column 3 that the estimated impact of inter-industry offshoring and inshoring confirms our basic result. It suggests that the domestic supply chain may act as a vehicle for internationalisation effects through upstream offshoring.

Supply Chain Position. Fally (2011) finds a large shift of value-added towards final stages of production, i.e. relatively downstream. He further shows that developed countries have a comparative advantage in goods that involve fewer production stages and goods that are closer to final demand.[20] This is also in line with Antràs et al. (2012), who show that a better rule of law, strong financial development, and relative skill intensity abundance are correlated with a higher propensity to export in relatively more downstream industries. This translates to the fact that relatively downstream industries both sell domestically and export output for $final$ use more intensively. Conversely, this implies that relatively less output is expected to 'be left' for domestic exchange in relatively downstream industries.

As a result, more domestic relationships will be generated in relatively upstream compared to relatively downstream industries. Therefore, we expect a larger potential for inter-industry effects in relatively upstream industries. To account for possible heterogeneity in the absorption of learning effects from inter-industry linkages, we generate an industry-level measure of relative supply chain position as in Fally (2011) and Antràs et al. (2012) using WIOD. This measure of industry upstreamness gives the average 'distance' of each industry from final use. We rank industries as relatively upstream or downstream based on the median value of the distribution of the upstreamness measure (see Table 3.D.2 in Appendix 3.D).

Columns 4 and 5 in Table 3.4 present results for relatively upstream or downstream industries, respectively. The expected heterogeneity of results between industries with different supply chain positions is confirmed. On the one hand, firms in relatively upstream industries (column 4) experience significant productivity effects of upstream inshoring,

[20] The latter is consistent with the predictions of Costinot et al. (2013).

which are larger in terms of point estimates, compared to the the basic specification. On the other hand, firms in relatively downstream industries do not experience any significant effects from inter-industry offshoring and inshoring.

High-skill vs Low-skill. Fally (2011) finds that R&D intensive industries have become relatively less fragmented over time. What is more, innovative industries have been found to rely less intensively on outsourcing (see Acemoglu et al., 2007, 2010). Therefore, relationship-specific learning that depends on links between firms through the exchange of intermediate inputs will be more limited in high-tech industries where such relationships are less prevalent. In columns 6 and 7 we split the sample of relatively upstream industries in high and low-skill intensive industries, on the basis of information available in the WIOD.[21] Upstream and low-skill intensive industries are expected to generate relatively more intermediate input based relationships than upstream and high-skill ones. Therefore, firms in low-skill intensive industries may be expected to experience stronger productivity effects from inter-industry offshoring and inshoring on average.

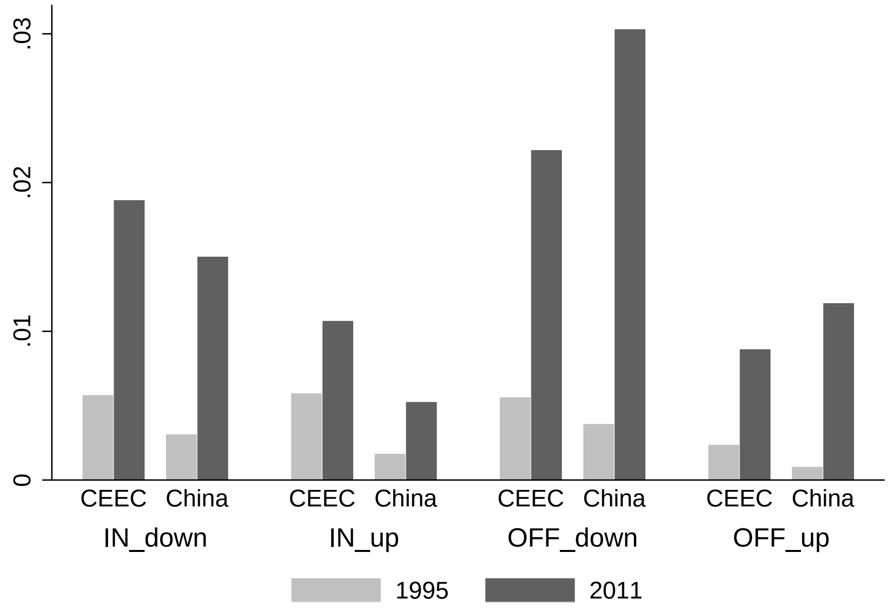
From columns 6 and 7 one can infer that only upstream and low-skill intensive industries experience upstream inshoring productivity effects. In upstream and high-skill intensive industries we detect no effects of indirect international supply chain participation.

China and Eastern Europe. Finally, we consider a geographical split of the partner countries of the inter-industry offshoring and inshoring measures. Like all Western European countries, Belgium has been confronted with two dramatic changes in the international trade environment. One is China's accession to the WTO and the other is the collapse of communism. Both events led to increasing trade opportunities with China and Eastern Europe, respectively. Figure 3.4 illustrates the evolution of downstream and upstream offshoring and inshoring related to China and Eastern Europe (CEEC).[22] China and CEEC have both become more important supply chain partners for Belgium. Although China and CEEC are not that important in level terms, they do account for a substantial increase and a considerable compositional effect over the period considered.

[21] High and Low-skill intensity is computed from the Socio-economic Accounts in the WIOD using total hours worked by high-skilled persons engaged over hours worked by medium and low-skilled persons engaged. High-skill intensive industries are defined based on the median value of the distribution of average high-skill to low-skill ratios for each industry over the period considered. High-skill includes industries with CPA: 3, 4, 5, 13, 14, 15, 16 and Low-skill includes industries with CPA: 6, 7, 8, 9, 10, 11, 12.

[22] Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia.

Figure 3.4: Inter-industry offshoring to and inshoring from China or CEEC



Source: Authors' calculations based on WIOD

Table 3.5: TFP effects from inter-industry offshoring and inshoring and the impact of China and CEEC

	(1a) *non-China non-CEEC*	(1b) *China*	(1c) *CEEC*
OFF_down_{jt-1}	-0.042	-0.666	2.623***
	(0.079)	(0.669)	(0.589)
IN_up_{jt-1}	0.282***	-6.015***	-1.193**
	(0.072)	(2.110)	(0.606)
OFF_up_{jt-1}	-0.794**	23.192***	-2.354
	(0.355)	(3.886)	(2.519)
IN_down_{jt-1}	0.057	-0.221	-1.196
	(0.087)	(0.965)	(0.912)
Observations			25463

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The regression includes intra-industry offshoring and inshoring split into rest-of-world (1a), China (1b) and CEEC (1c), and dummies for multinational (MNC), domestic shareholder (SHH^{BE}) and domestic subsidiary (SUB^{BE}) presence. Standard errors are block-bootstrapped with 500 replications over the GNR two-step estimation procedure and are reported in parentheses below point estimates.

In Table 3.5 we estimate our basic model, but now split the proxies according to the partner region. Column 1a excludes China and CEEC from the measures whereas columns 1b and 1c single out China and CEEC, respectively. With respect to our main result we find that the positive effect of upstream inshoring is driven by exports to destination markets other than China and CEEC, which are almost exclusively advanced markets. Exports of intermediates to China or CEEC even seem to have a negative impact along the domestic supply chain. We think of this as an indication that the availability of higher quality intermediates is the main channel through which productivity is affected because quality requirements will differ between advanced destination countries on the one hand and China and CEEC on the other. Note that the differences in the magnitudes of the estimated effects come from the fact that the variables of interest are not standardised. These are variables that are by construction between zero and one and are 'demeaned' from the inclusion of industry and year fixed effects in the regression. However, for inference we also need to consider their standard deviations.

Upstream offshoring to China is associated with a significantly higher productivity of domestic clients of such industries; there is no such an effect for CEEC. This could be reconciled with the idea that upstream industries import cheaper intermediate inputs from China that allow them to economise and subsequently push down the marginal cost curves of their downstream clients. For the case of CEEC such costs could be higher relative to China, especially when thinking about their unit labour costs and institutional environment.

Belgian firms do seem to have reacted to downstream offshoring to CEEC, i.e. import competition, by becoming more productive, but no such effect can be found for China. This can be reconciled by the result of Merlevede and Michel (2013), where downstream offshoring has a robust negative effect on employment. Therefore, Belgian firms are pushed to increase their productivity in order to outweigh the negative effect on labour demand from 'indirect' import competition. This effect does not appear for the case of China since the presence of tougher geographical and institutional barriers potentially induces the products that are offshored by downstream firms to be direct substitutes (instead of complements) to the products that are domestically outsourced from upstream firms. However, as shown in the previous section, this last set of findings is not robust and thus should be taken with a grain of salt.

3.6 Conclusion

A large literature has examined the relationship between export and import behaviour, on the one hand, and productivity, on the other. Yet, notwithstanding a substantial amount of research on the direct productivity effects of firms' or industries' offshoring behaviour, potential indirect or spillover productivity effects of internationalisation have received less attention. We analyse potential productivity effects for a given firm that are associated with the internationalisation behaviour of other firms in the domestic economy. Since sharing new knowledge with related parties along the supply chain is more likely than sharing it with competitors, we focus on the effects of internationalisation by local clients and suppliers of a given firm. Local firms may then experience indirect productivity effects of internationalisation through participation in the domestic supply chain.

We define four 'channels' of possible inter-industry productivity effects for a given firm: its local client may (1) source its intermediates from abroad (*downstream offshoring*) or (2) export its output (*downstream inshoring*). Additionally, a given firm's local supplier may also (3) export intermediates that the given firm sources (*upstream inshoring*) or (4) import intermediates itself (*upstream offshoring*).

We combine firm level data for manufacturing firms for the period 1995-2011 with I-O tables to investigate potential productivity effects along the supply chain driven by trade in intermediates in linked industries for the case of Belgium. I-O tables are used to construct industry-level proxies for inter-industry offshoring and inshoring intensities. No clear upward trend is detected in these variables unless we separately consider the case of China and Eastern Europe as trade partners, where there is a considerable increase.

Empirically, we model potential productivity effects from inter-industry offshoring and inshoring as a learning process. Within a production function system we allow past experience from inter-industry offshoring and inshoring to affect future productivity. Therefore, productivity measurement is a core element in our analysis. Recent literature typically relies on proxy variable methods which attempt to solve for the endogeneity problem that arises from firms choosing inputs while knowing their TFP. Despite their popularity, proxy variable methods suffer from identification issues when the production function contains at least one flexible input, e.g. materials. To circumvent this problem, applied economists focus on value-added production functions. As a result TFP suffers from a 'value-added bias' which leads to overstated dispersion and heterogeneity. To be able to correctly identify a gross-output production function, we use the estimator proposed by GNR, that controls for both the endogeneity and value-added bias. Additionally, we point to a common specification bias in applied work when ignoring the dynamic nature of productivity.

Our results can be summarised as follows. First, we demonstrate and confirm important biases arising from ignoring the dynamic nature of productivity and specifying a value-added rather than a gross-output production function. Failing to correct for these biases may thus result in false conclusions.

Second, only upstream inshoring, i.e. the export of intermediates by a given firm's local suppliers, appears to be a robust channel of inter-industry productivity effects in Belgium. Sourcing from industries that also export these intermediates is associated with higher productivity levels of a given firm. This effect likely stems from access to better intermediates that are also exported. On the basis of our preferred point estimate, a one standard deviation increase in upstream inshoring is associated with a productivity increase of 0.45% in the short run and 8.73% in the long run.

In support of our result, we find these effects to be stronger for those firms and industries that are less likely to be directly internationally involved. The effect is more prominent for smaller firms, for firms with non-multinational status, and for firms in relatively upstream and/or low-skill intensive industries. Finally, we find no such effects if the destination of exported intermediates is China or Eastern Europe. Therefore, positive productivity effects that result from access to increased quality and variety of locally available inputs because of local supply chain participation are strengthened. This holds as long as intermediate goods exports face lower quality requirements when destined to China and Eastern Europe compared to more advanced economies.

This paper provides a new channel through which internationalisation can affect firms. This is particularly insightful for two reasons. First, our analysis suggests that policy makers should facilitate trade with more developed economies in order to minimise the negative indirect (through the domestic supply chain) productivity effects of trading with less developed countries. Second, we expect our findings to motivate theoretical models on firm heterogeneity, supply chains and trade in order to improve our understanding of the exact mechanisms behind our empirical findings. Such models would allow us to generate counterfactual predictions about patterns of trade, production and productivity from changes in policies related to internationalisation.

Appendix 3.A Construction of Proxies

3.A.1 Intra-industry Offshoring and Inshoring

Based on the seminal work of Feenstra and Hanson (1996), intra-industry offshoring intensity is proxied as the share of imported intermediate inputs over total intermediate inputs used in the industry:

$$off_{jt} = \frac{MII_{jt}}{TII_{jt}} \tag{3.10}$$

where MII_{jt} refers to imported intermediate inputs and TII_{jt} refers to total non-energy intermediate inputs of industry j at time t.[23] Due to data limitations, our definition of offshoring also includes production transfers within multinationals (vertical FDI), where intermediate inputs flow between affiliated companies. Proxies are computed using symmetric IO-tables from the WIOD.

For a symmetric treatment of the inter-industry effects of internationalisation below it would be incorrect to restrict our attention to offshoring. We also need to examine inshoring defined as export of intermediate inputs to both affiliated and unaffiliated firms in a foreign country.

We proxy inshoring in the same vein as offshoring:

$$in_{jt} = \frac{XY_{jft}}{TY_{jt}} \tag{3.11}$$

where XY_{jft} is industry j's output exported specifically for intermediate input use and TY_{jt} is industry j's total output supplied for intermediate input use to both foreign and domestic firms.

3.A.1.1 Downstream Offshoring

The previous measure of offshoring is limited to the effects of offshoring within an industry. For example, how are firms in the Manufacture of Rubber and Plastics affected by offshoring? Clearly, this measure ignores any inter-industry linkages. Firms in the Manufacture of Rubber and Plastics industry also supply intermediate inputs to domestic firms in the Manufacture of Machinery and Equipment industry. In turn, the Manufacture

[23]Feenstra and Hanson (1999) distinguish between narrow (intermediates from the same industry) and broad (all imported intermediates) offshoring.

of Machinery and Equipment industry may decide to (partly) offshore these intermediate inputs supplied by the Manufacture of Rubber and Plastics industry. Such a change in the offshoring behaviour of firms in the downstream Manufacture of Machinery and Equipment industry is likely to affect the performance of firms in the upstream Manufacture of Rubber and Plastics.

To capture the effect transmitted to firms in the supplying industry from the offshoring activity undertaken by firms in downstream industries, we compute a proxy at the industry-level. This proxy was proposed by Merlevede and Michel (2013) and termed "downstream offshoring." Define a focal industry j, a downstream industry d and a set $P = (p^1, p^2, \ldots, p^N)$ of all products p indexed by $n = 1, \ldots, N$ that are produced in the economy.

From the supply tables, we retrieve the output product mix of firms in industry j, $P_j^{SUP} \subset P$, i.e. the output produced by firms in industry j. Likewise, from the use tables, we are able to retrieve the product mix of intermediate inputs purchased by domestic downstream industry d, $P_d^{USE} \subset P$. These are products that firms in industry d buy as intermediate inputs from domestic upstream industry j. All products produced by firms in industry j that are purchased as intermediate inputs by firms in industry d are represented by the intersection of the two previous sets of products, $P_{jd} = P_j^{SUP} \cap P_d^{USE}$. Given that the WIOD tables contain 59 product categories and 35 industries, P_{jd} will contain more than one product in some combinations of jd. This extra level of detail captures the importance of secondary output as well.[24]

Firms in downstream industry d choose between domestic sourcing or offshoring any of the intermediate inputs n. Hence, if for example d increasingly offshores product $p^n \subset P_{jd}$, then firms in industry j would face a demand shock. The offshoring intensity for each matched product p^n by each dowstream industry d is computed as in (3.10) from the international use tables:

$$off_{dnt} = \frac{MII_{dnt}}{TII_{dnt}} \tag{3.12}$$

[24]There is no consensus in the literature over which sectors should be included in the measures. Our benchmark proxy contains products from all sectors excluding: Agriculture, Hunting, Forestry and Fishing; Mining and Quarrying; Coke, Refined Petroleum and Nuclear Fuel; Electricity Gas and Water Supply; Construction; Hotels and Restaurants; Financial Intermediation; Public Admin. and Defence; Education; Health and Social Work; Other Community, Social and Personal Services; and Private Households with Employed Persons.

where MII_{dnt} is imported intermediate input n and TII_{dnt} is total intermediate input n used in industry d.

The extent to which downstream industry d's imports of intermediate products n affect focal industry j is measured as a weighted sum of off_{dnt} for all products n that j supplies as intermediate inputs to d that are, in turn, also potentially offshored by the latter, P_{jd}:

$$\Phi_{jdt} = \sum_{p^n \subset P_{jd}} \delta_{jnt} \mathit{off}_{dnt} \tag{3.13}$$

where the weight $\delta_{jnt} = Y_{jnt} / \sum_{p^n \subset P_j^{SUP}} Y_{jnt}$, captures the relative importance of output product n for industry j. It is computed as the share of industry j's final product p^n in its output mix P_j^{SUP}, using data from international supply tables.

As a final step, downstream offshoring for industry j is defined as the weighted sum of Φ_{jdt} for all downstream industries d that j supplies with intermediate inputs:

$$Down\_off_{jt} = \sum_{d \neq j} \theta_{jdt} \Phi_{jdt} \tag{3.14}$$

where the weight $\theta_{jdt} = Y_{jdt} / \sum_d Y_{jdt}$, is computed from the WIOD and denotes the relative importance of domestic supply to downstream industry d in total domestic downstream supply. Combinations with $j = d$ are excluded, as they refer to intra-industry offshoring that is already captured from traditional offshoring measure off_{jt} (3.10). Further, we fix each θ_{jdt} to its 1995 value, the start year of the sample, i.e. θ_{jd1995}. This eliminates distortions in the measure due to differences in the evolution of offshoring across time and industries.

Overall, $Down\_\mathit{off}_{jt}^{\theta_{1995}}$ is our baseline proxy for downstream offshoring, where higher values are interpreted as industry j facing higher downstream offshoring.[25]

3.A.1.2 Upstream Inshoring

In a similar spirit we define upstream inshoring for a focal firm as sourcing intermediates from (a firm in) an industry that also exports the same intermediate goods to both affiliated and unaffiliated firms in foreign countries. Suppose that the Manufacture of Office Machinery and Computers industry buys intermediate inputs from the Manufacture

[25] For brevity, we suppress the index θ_{1995} for the rest of the cases.

of Computer and Related Services industry. When the latter increases its exports of these intermediate inputs, i.e. inshores, this potentially affects the productivity of firms in the Manufacture of Office Machinery and Computers industry. Mechanisms generating such effects may range from the availability of increased quality of intermediate inputs to innovation or knowledge spillovers.

Firms in upstream industry u now choose a combination of domestic supply and exports of the intermediate inputs n they produce. As above, we are able to obtain the inshoring intensity for each matched product p^n between a focal industry j and each upstream industry u from the use tables:

$$in_{unt} = \frac{EII_{unt}}{TII_{unt}} \tag{3.15}$$

where EII_{unt} is the export value of intermediate input n and TII_{unt} is the total production of intermediate input n in industry u.

The extent to which export of intermediate products n by upstream industry u affect focal industry j is measured as a weighted sum of in_{unt} for all products n that j buys as intermediate inputs from upstream industry u (product set P_{ju}):

$$\Psi_{jut} = \sum_{p^n \subset P_{ju}} \gamma_{jnt} in_{unt} \tag{3.16}$$

where the weight $\gamma_{jnt} = Y_{jnt} / \sum_{p^n \subset P_j^{INP}} Y_{jnt}$ captures the relative importance of intermediate input n for industry j. It is computed as the share of intermediate input p^n in industry j's input mix P_j^{INP} using data retrieved from supply tables.

Finally, our measure for upstream inshoring aggregates Ψ_{jut} over all upstream industries u and captures inter-industry effects of inshoring through client-supplier linkages as:

$$IN\_up_{jt} = \sum_{u \neq j} \zeta_{jut} \Psi_{jut} \tag{3.17}$$

where ζ_{jut} is defined as the proportion of industry j's domestically sourced intermediate inputs from upstream industry u at time t.

3.A.1.3 Upstream offshoring and Downstream Inshoring

In addition to downstream offshoring and upstream inshoring that are based on the direct exchange of 'common' products, we propose two new measures for indirect internationalisation through domestic supply chain participation. In this case no product-specific links are at play. However, in the context of increasing supply chain fragmentation, offshoring or inshoring in a previous or subsequent stage of the supply chain may result in more indirect productivity spillover effects. To analyse such inter-industry effects, we define measures for upstream offshoring and downstream inshoring as follows:

$$OFF\_up_{jt} = \sum_{u \neq j} \zeta_{jut} \Omega_{jut} \tag{3.18}$$

where ζ_{jut} is defined as before and Ω_{jut} is the offshoring intensity in industry u, averaged over all products, since in this case there is no direct product link between industry j and u. For downstream inshoring we have:

$$IN\_down_{jt} = \sum_{d \neq j} \theta_{jdt} \Theta_{jdt} \tag{3.19}$$

where Θ_{jdt} measures the inshoring intensities of downstream industry d and θ_{jdt} is defined as above. Upstream offshoring effects originate from the import of intermediate inputs by the focal firm's suppliers; downstream inshoring effects potentially result from the demand for increased quality of intermediate inputs from the downstream industry.

Appendix 3.B GNR Two-step Estimation Procedure

This section serves as an overview of the basic steps and assumptions of the GNR estimation procedure. For a detailed and complete description refer to GNR.

This case considers the classic environment of perfect competition in both input and output markets. Capital is a predetermined input and therefore chosen one year prior to the realisation of productivity ($t-1$). Labour is assumed to be a variable input, but subject to adjustment costs. In this case, labour is chosen during the realisation of productivity, ω_{it}, i.e. between $t-1$ and t. The only flexible input in the specification is material, assumed to freely adjust in each period (variable) and have no dynamic implications (static).

Conditional on the state variables and other firm characteristics, a firm's static profit maximisation problem yields the first order condition with respect to the flexible input, material:

$$P_t^M = P_t \frac{\partial}{\partial M_t} F(L_{it}, K_{it}, M_{it}) \mathrm{e}_{it}^{\omega} \mathcal{E} \tag{3.20}$$

where P_t^M and P_t are the price of material and output respectively. Under perfect competition in input and output markets, they are constant across firms within the same sector but can vary across time. By the time firms make their annual decisions, ex-post shock ϵ_{it} is not in their information set. Hence, firms create expectations that are similar across firms, $\mathcal{E} = E(\mathrm{e}^{\epsilon_{it}})$.[26] It is important to account and correct for this term since ignoring it, i.e. $\mathcal{E} = 1$, inherently implies that we move from the mean to the median central tendency of $\mathrm{e}^{\epsilon_{it}}$ (see Goldberger, 1968).

Combining (3.20) with (3.5) and re-arranging terms, we retrieve a share equation:

$$s_{it} = ln\Big(\ G(L_{it}, K_{it}, M_{it})\ \Big) + ln\mathcal{E} - \epsilon_{it} \tag{3.21}$$

where s_{it} is the log of the nominal share of intermediate inputs and $G(L_{it}, K_{it}, M_{it}) = \frac{\partial}{\partial m_{it}} lnf(l_{it}, k_{it}, m_{it})$ is the output elasticity of the flexible input, material. Note that the share equation is net of the productivity term ω_{it}, inducing the transmission bias.

[26]We inherently assume that the existence of any measurement error is symmetric across firms and thus does not affect our results.

3.B.1 Step One

A Non Linear Least Squares estimation of the share equation (3.21) is applied, with:

$$G(L_{it}, K_{it}, M_{it})\mathcal{E} = \sum_{r_l+r_k+r_m \leq r} \gamma'_{r_l,r_k,r_m} l_{it}^{r_l} k_{it}^{r_k} m_{it}^{r_m}, \ with \ \ r_l, r_k, r_m \geq 0 \tag{3.22}$$

approximated by a polynomial series estimator of order r. This step identifies ϵ_{it} (hence $\mathcal{E}$) and the output elasticity of the flexible input material.

3.B.2 Step Two

By integrating up the output elasticity of the flexible input:

$$\int \frac{G(L_{it}, K_{it}, M_{it})}{M_{it}} dM_{it} = ln\Big(F(L_{it}, K_{it}, M_{it})\Big) + \mathcal{B}(L_{it}, K_{it}) \tag{3.23}$$

we identify the production function up to an unknown constant of integration. By differencing it with the production function (3.5) we retrieve the following equation for productivity:

$$\omega_{it} = \mathcal{Y}_{it} + \mathcal{B}(L_{it}, K_{it}) \tag{3.24}$$

where $\mathcal{Y}_{it}$ is the log of the expected output net of the computed integral (3.23) and $\mathcal{B}(L_{it}, K_{it})$ is the constant of integration, approximated by a polynomial series estimator of degree ν:

$$\mathcal{B}(L_{it}, K_{it}) = \sum_{\nu_l+\nu_k \leq \nu} \alpha_{\nu_l,\nu_k} l_{it}^{\nu_l} k_{it}^{\nu_k}, \ with \ \ \nu_l, \nu_k > 0 \tag{3.25}$$

To proceed we exploit the assumption over the law of motion for productivity. Similar to the seminal work of Olley and Pakes (1996), an 'exogenous' first order Markov process is assumed, $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$. However, 'exogeneity' is relaxed in order to accommodate concerns raised by Aw et al. (2008); De Loecker (2013); Doraszelski and Jaumandreu (2013) and De Loecker and Goldberg (2014). Lagged and observable variables, such as our measures of interest, are allowed to affect current productivity outcomes:

$$\omega_{it} = g(\omega_{it-1}, proxies_{jt-1}, X_{it-1}, \alpha_t, \alpha_j, \alpha_r) + \xi_{it} \tag{3.26}$$

where $X_{it-1} = (MNC_{it-1}, SUB_{it-1}^{BE}, SHH_{it-1}^{BE})$. Also, time, industry and region dummies are included to control for shocks varying over time and across industries and regions, respectively.[27] We can now express the innovation of productivity, ξ_{it}, as a function of the parameters of the constant of integral to be estimated $\xi_{it}(\alpha)$, by non parametrically regressing $\omega_{it}(\alpha)$ on $g(\omega_{it-1}, proxies_{jt-1}, X_{it-1}, \alpha_t, \alpha_j, \alpha_r)$.

This step proceeds with an iterative GMM. The moments used are $E[\xi_{it}(\alpha) \otimes n'_{it}] = 0$. The orthogonality conditions depend on the timing assumption of inputs. For the case of a polynomial of degree two, $\nu = 2$, for the constant of integration (3.25), we get:

$$n_{it} = (k_{it}, l_{it-1}, k_{it}^2, l_{it-1}^2, k_{it} l_{it-1}) \tag{3.27}$$

where capital is a predetermined input chosen one year prior (orthogonal to the innovation of productivity) and labour adjusts within the year (correlated with the innovation of productivity, thus use lagged values).

For a polynomial of degree two for both (3.22) and (3.25) the estimated gross-output production function is:

$$\begin{aligned} y_{it} = \{&\gamma_0 + \gamma_k k_{it} + \gamma_l l_{it} + \frac{\gamma_m}{2} m_{it} + \gamma_{ll} l_{it}^2 + \gamma_{kk} k_{it}^2 + \frac{\gamma_{mm}}{3} m_{it}^2 \\ &+ \gamma_{lk} l_{it} k_{it} + \gamma_{lm} l_{it} m_{it} + \frac{\gamma_{lm}}{2} l_{it} m_{it} + \frac{\gamma_{km}}{2} k_{it} m_{it}\}\, m_{it} \\ &- \alpha_l l_{it} - \alpha_k k_{it} - \alpha_{ll}^2 l_{it} - \alpha_{kk}^2 k_{it} + \omega_{it} + \epsilon_{it} \end{aligned} \tag{3.28}$$

Using estimates of the production function coefficients $\hat{\gamma}$ and $\hat{\alpha}$ at the CPA industry level, we retrieve productivity estimates $\hat{\omega}_{it}$ for firm i in industry j at time t from equation (3.24).

From this two-step procedure, we retrieve estimates of the production function coefficients that allow us to compute productivity $\hat{\omega}_{it}$ and other relevant variables, i.e output elasticities of inputs and returns to scale for firm i at time t, using (3.28).

In addition, within the second step, we can also directly identify the effects on future productivity of firms from inter-industry offshoring and inshoring $\left(\frac{\partial g(\cdot)}{\partial proxies_{jt-1}}\right)$.

[27] For comparability with the models considered in the main text we use a linear specification of $g(\cdot)$.

Appendix 3.C ACF Two-step Estimation Procedure

This section provides an overview of the basic steps and assumptions in the ACF estimation procedure. For a detailed and complete description refer to ACF. This procedure controls for collinearity problems encountered in Levinsohn and Petrin (2003). Assumptions imposed about competition and timing of firms' decisions are as in the previous section. The only difference is that we now use a value-added production function, $VA_{it} = Y_{it} - M_{it} = F(K_{it}, L_{it})\mathrm{e}^{\omega_{it}}$. A translog specification is considered based on its high application frequency in empirical research. In logs, the production function to be estimated is:

$$va_{it} = \gamma_k k_{it} + \gamma_l l_{it} + \gamma_{kk} k_{it}^2 + \gamma_{ll} l_{it}^2 + \gamma_{kl} kl_{it} + \omega_{it} + \epsilon_{it} \tag{3.29}$$

where va_{it} is the log of double deflated value-added for firm i at time t.

Conditional on the state variables and other firm characteristics, firm's static profit maximisation yields material input demand $m_{it} = m(l_{it}, k_{it}, m_{it})$. To control for unobserved productivity, ω_{it}, we use the inverted intermediate input demand $\omega_{it} = m^{-1}(l_{it}, k_{it}, m_{it})$. To approximate the latter, we use a third-order polynomial of l_{it}, k_{it}, and m_{it}. Time, industry and region dummies are also included additively controlling for shocks varying over time and across industries and regions.[28]

First stage regression $y_{it} = \phi(l_{it}, k_{it}, m_{it}, z_{it}) + \epsilon_{it}$ delivers a measure of output purged from ex-post shocks and measurement errors in output, $\hat{\phi}_{it}$. Continuing, productivity can be expressed as a function of the production function parameters γ to be estimated:

$$\omega_{it}(\gamma) = \hat{\phi}_{it} - x_{it}\gamma \tag{3.30}$$

where $x_{it} = (l_{it}, k_{it})$. As before, we can express the innovation from the law of motion of productivity as a function of the production function parameters to be estimated $\xi_{it}(\gamma)$, by regressing ω_{it} on $g_{it}(\omega_{it-1}, proxies_{jt-1}, X_{it-1}, \alpha_t, \alpha_j, \alpha_r)$.

In step two, the coefficients of the production function are estimated with an iterative GMM procedure. The moments used are $E[\xi_{it}(\gamma) \otimes n'_{it}] = 0$, where $n_{it} =$

[28] Ideally, to exclude the possibility of other unobservable factors that would violate the scalar unobservability assumption, we should use as many relevant observable variables as possible (with the parameter space restriction in mind).

$(k_{it}, l_{it-1}, k_{it}^2, l_{it-1}^2, k_{it}l_{it-1})$ is based on the same timing assumptions for capital and labour assumed in Appendix 3.B. As before, within this two-step procedure, we can directly identify both the production function coefficients and the effects on future productivity from inter-industry offshoring and inshoring $\left(\frac{\partial g(\cdot)}{\partial proxies_{jt-1}}\right)$.

Appendix 3.D Additional Figures and Tables

Table 3.D.1: List of CPA and NACE 2-digit (Rev.1.1) industries for manufacturing sector

CPA	NACE	Description
3	15t16	Manufacture of Food, Beverages and Tobacco
4	17t18	Manufacture of Textiles and Textile Products
6	20	Manufacture of Wood and Products of Wood and Cork
7	21t22	Manufacture of Pulp, Paper, Printing and Publishing
9	24	Manufacture of Chemicals and Chemical Products
10	25	Manufacture of Rubber and Plastic products
11	26	Manufacture of Other Non-Metallic Mineral Products
12	27t28	Manufacture of Basic Metals And Fabricated Metal Products
13	29	Manufacture of Machinery and Equipment n.e.c.
14	30t33	Manufacture of Electrical and Optical Equipment
15	34t35	Manufacture of Transport Equipment
16	36t37	Manufacture of Manufacturing, n.e.c.;Recycling

Table 3.D.2: Upstreamness measure

Production Line Position	CPA	Mean
Relatively Downstream	8	2.42
	3	2.48
	9	2.62
	5	2.63
	13	2.72
	14	2.74
	15	2.80
Relatively Upstream	4	2.82
	11	2.94
	10	2.96
	7	2.97
	16	3.13
	6	3.24
	12	3.43

Notes: Computed as in Fally (2011) and Antràs et al. (2012) using the WIOD. Mean represents the mean value from 1995 to 2011 for each industry and is used to rank industries on their relative position in the production line.

4

Market Imperfections, Trade and Firm Performance*

4.1 Introduction

Firms' demand for various inputs adjust more slowly than demand shocks to these inputs themselves. Such sluggishness is mainly attributed to frictions in the input market. On the one hand, institutions set a restrictive regulatory environment in which firms operate. Typical regulations cover: firing costs; minimum wages; employment protection; payroll tax rate; labour unions; and access to finance and investment subsidies. On the other hand, general characteristics of the input market affect the way firms adjust their inputs. Such characteristics include: screening of employees; labour market mobility; installation costs of new capital; indivisibilities in capital; training costs; and costs of posting vacancies. Therefore, even firms operating in economies with the most flexible input markets face adjustment costs that impact both aggregate and firm-level outcomes (Hamermesh and Pfann, 1996).

*I thank participants at DEGIT Sept. 2016, ETSG Sept. 2016, Ghent University Internal Seminar Sept. 2016 and 9th FIW Dec. 2016 for their comments and suggestions. Special thanks are extended to Jan De Loecker, Ruben Dewitte, Gerdie Everaert, Rebecca Freeman, Joep Konings, Kalina Manova, Bruno Merlevede, Peter Neary, Nina Pavcnik, Gianmarco Ottaviano, Glenn Rayp, Ariell Reshef, David A. Rivers, Mark Roberts, Thomas Sampson, Johannes Schmieder, Felix Tintelnot and Gonzague Vannoorenberghe.

With this in mind, it becomes clear why models that assume homogeneous and perfect labour market conditions perform poorly. In response, the literature has also introduced models with input market rigidities to explain patterns observed in aggregate variables such as: employment; unemployment; job turnover; wages; investment; divestment; and capital irreversibilities.[1] Similarly, the latest developments in theoretical modelling provide researchers with the appropriate analytical tools to model the role of specific input market rigidities (e.g. severance payments, search and matching frictions, and credit constraints) on the decisions and dynamics of the firm.[2]

International trade literature has also benefited from these advancements by incorporating labour market frictions in models with firm heterogeneity and trade. These models provide a theoretical explanation of how specific types of labour market rigidities (e.g. search frictions, matching frictions or severance payments) can reconcile patterns observed in an economy with trade and trade frictions. The focus so far has been on outcomes such as: employment; investment; wage inequality; and welfare changes within and between industries or countries.[3]

Yet, not much has been said about productivity. The majority of the aforementioned theoretical literature treats input market rigidities as financial constraints that affect investment decisions and thus productivity of the firm. This relationship is amplified by the presence of trade and trade frictions. However, all these models use a simplistic measure of labour productivity and results are driven by certain types of input market frictions. This difficulty arises from the fact that most theoretical models consider only one type of input market rigidity at a time (e.g. matching frictions) because of 'analytical convenience.' This excludes other possibly equally significant interacting sources of rigidities (e.g. search frictions or severance payments).

Furthermore, most of the empirical work is performed at the aggregate level (i.e. country/industry) and with no robust findings at the micro level (i.e. firm/plant). One exception is Dobbelaere and Vancauteren (2014) who use a relatively flexible approach to express input market frictions and estimate their effects on productivity. However, they

[1]From the non-exhaustive list, see: Hopenhayn and Rogerson (1993); Alvarez and Veracierto (2001); Lagos (2006); Hobijn and Şahin (2013); and Aguirregabiria and Alonso-Borrego (2014).

[2]See Autor et al. (2007); Koeniger and Prat (2007); Dustmann et al. (2009); and Card et al. (2013).

[3]See Helpman et al. (2010b,a, 2011, 2016); Egger and Kreickemeier (2009); Felbermayr et al. (2011, 2014); Helpman and Itskhoki (2010); Fajgelbaum (2013); and Coşar et al. (2016).

still focus on labour market frictions at the industry level, masking possible heterogeneity and interaction effects with capital market frictions. Overall, both the theoretical and empirical literature have not yet introduced a consistent way of expressing all existing input market rigidities in a single firm-level measure. This reduces the flexibility to characterise their overall impact on firm level performance.

I bridge this gap by estimating the impact of input market frictions on firm performance. To do so, I exploit the optimal decisions from the dynamic problem of a firm with adjustment costs. This idea is not new in the literature and is in line with the work of Petrin and Sivadasan (2006, 2013) who use the first order conditions from the dynamic problem of the firm to construct a statistic to measure economic inefficiency from the presence of non-neoclassical components, i.e. hiring, firing, search costs, capital adjustment costs, taxes, subsidies, hold-up and other contracting problems, non-optimal managerial behaviour, and markups. Also, it is conceptually similar to the seminal work of Caballero and Engel (1993) who show that the gap between the observed and forecasted optimal level of employment is related to the probability of adjusting labour.[4]

I capture firm-level frictions for the non-flexible inputs as the wedge between the marginal revenue product and the marginal cost of each input, respectively. This wedge departs from the neoclassical assumption of freely adjustable inputs and is driven by the presence of costs that adjust to the non-flexible inputs. Such a modification allows frictions in the input market to be expressed as a function of variables typically observed in most micro-level datasets and parameters of the production function.

Heterogeneity is expected since firm attributes shape idiosyncrasies on the firm's cost function.[5] This would be true even if all policy-related input market rigidities were to apply at the country level. Overall, I consider these measures as indicators of how costly it is for each firm to adjust its non-flexible inputs, directly reflecting the level of frictions in the input market. In this paper, I assume that material inputs adjust freely while capital and labour face adjustment costs from the presence of frictions. This translates to the respective empirical measures for labour market frictions (henceforth LMF) and capital market frictions (henceforth KMF).

[4]For more on the gaps see Gali et al. (2007); Eslava et al. (2010); and Caballero et al. (2013).

[5]Examples of firm attributes include: training costs for new employers; composition of labour in the firm; installation time for new capital; posting of new vacancies; screening process of employees; mobility costs of employees; etc.

Introducing these measures in any typical proxy variable method of estimating production functions, I can directly estimate the effects of LMF and KMF on the future productivity of firms as well as the parameters of the production function.[6] Empirically, I model potential productivity effects from rigidities in the input market as a learning process. I allow past experience from LMF and KMF to affect the future productivity of firms, similar to Aw et al. (2008) and De Loecker (2013).

For the analysis, I use a rich dataset with firm-level information from the manufacturing sector of 16 EU countries for the period 2002-2007. The extensive data coverage across EU countries allows me to draw conclusions with external validity and also uncover possible patterns by exploiting variation across countries and industries.

On the one hand, I find that increases in labour market frictions positively affect the future productivity of firms. This is in line with the idea that firms face higher costs for adjusting their stock of labour during periods of increased labour market rigidities. Therefore, they are forced to find alternative channels to substitute the costly adjustment of labour to meet demand for their final output. Such channels may refer to costless improvements in management practices and organisational forms, i.e. intrinsic motivation (arising from the innate value of the work for the individual).

More specifically, during periods of increased frictions in the labour market, firms face monetary constraints that reduce their ability to extrinsically motivate their employees.[7] Therefore, firms turn to intrinsic motivation as a potential non-monetary instrument that increases the creativity, transfer of tacit knowledge and multi-tasking ability of employees (Osterloh and Frey, 2000). However, intrinsic motivation is a successful mechanism only in the short-run. In the long-run,"crowding-out" from the presence of external intervention via monetary incentives dominates (Frey et al., 1996; Kubon-Gilke, 1998; Frey and Jegen, 2001). Overall, the increase in future productivity of firms comes from the more efficient use of costless intangible inputs due to the slow or non-adjustment of tangible inputs, i.e. labour.

On the other hand, increases in capital market frictions induce significant productivity effects but are less prevalent and weaker than before. In periods of increased capital

[6]Under a more restrictive set of assumptions and structure, this approach can also be applied to dynamic panel methods.

[7]This arises from firm's desire to obtain outcomes that are separate from the work itself

market frictions it is very costly for firms to replace or update their existing capital. Therefore, they have to come up with costless ways of reconfiguring their existing capital in order to make their production processes more efficient to meet demand. As before, intrinsic motivation of employees is a non-monetary mechanism that results in creative ideas for reconfiguring capital. However, productivity improvements via this channel are less prevalent compared to the case of labour. This is reconciled by the fact that capital adjusts less freely than labour, as it is a tangible fixed asset. This is particularly true in the manufacturing sector: production lines face capacity constraints that are mainly relaxed when firms undertake new investments (e.g. new machineries or upgrading production processes) while labour can be managed more flexibly.

Continuing, I find that, in the face of increased labour market frictions, the future productivity of exporters increases by less than non-exporters. Openness makes firms more willing to incur the costs associated with adjusting their workforce (Coşar et al., 2016). Therefore, compared to non-exporters, they are less likely to reorganise their existing workforce despite the potential for relatively larger increases in future productivity. However, no significant effects appear when interacting capital market frictions with exporting behaviour, pointing again to the non-flexible nature of capital. On average, both exporting and non-exporting firms are equally constrained from capital market frictions.

The remainder of this paper is organised as follows: in Section 4.2 I first provide an overview of how I model imperfections in the input market. I then describe how I retrieve a firm-level measure that captures the presence of frictions in the capital and labour market. In Section 4.3 I provide the empirical methodology for identifying the productivity effects from labour and capital market frictions and in Section 4.4 I describe the data. Section 4.5 presents the main results. Finally, Section 4.6 concludes.

4.2 Market Imperfections

To introduce imperfections in the input market I include adjustment costs in a dynamic model of the firm. From the optimal decisions of the firm I express input market frictions as the wedge between the marginal revenue product and marginal cost of each input, respectively. This section provides the main steps and assumptions made. For a detailed analysis see Appendix 4.A.

Using capital (K_{it}), labour (L_{it}) and material (M_{it}) inputs, firm i in period t produces a non-storable output that is supplied in the output market under imperfect competition. The framework followed is general enough to cover the most common models of imperfect competition. More specifically, as shown by Epifani and Gancia (2011) and discussed below, such models refer to environments where firms produce homogeneous or differentiated goods and compete in quantity or price.

The periodical information set of the firm is denoted by $\mathcal{I}_{it}$ and includes any type of information that the firm considers when making its period input decisions. Capital is assumed to be a predetermined input and thus included in the firm's information set upon use in the period's production process, i.e. $\{K_{it}\} \in \mathcal{I}_{it}$. Capital accumulates, with a probability of one, according to $K_{it} = (1 - \delta_{it})K_{it-1} + I_{it-1}$, where δ_{it} is the rate of capital depreciation and I_{it-1} is investment in new capital. Labour is assumed to be a dynamic input, meaning that it is variable in period t ($L_{it} \notin \mathcal{I}_{it}$) and has dynamic implications ($\frac{\partial}{\partial L_{it-1}} L_{it} \neq 0$) from the presence of adjustment costs. The only flexible input is material that is variable in each period ($M_{it} \notin \mathcal{I}_{it}$) and has no dynamic implications ($\frac{\partial}{\partial M_{it-1}} M_{it} = 0$). Subtracting production costs from revenue I get the firm's profit function:

$$\begin{aligned} \Pi_{it}(A_{it}, K_{it}, K_{it+1}, L_{it-1}, L_{it}, M_{it}) =& R_{it}(A_{it}, K_{it}, L_{it}, M_{it}) - P^I_{it} I_{it} - P^L_{it} L_{it} - P^M_{it} M_{it} \\ & - C_{it}(A_{it}, K_{it}, K_{it+1}, L_{it-1}, L_{it}) \end{aligned} \tag{4.1}$$

where $R_{it}(\cdot)$ is the firm's revenue function, P^I_{it} is the direct purchase price of new capital, P^L_{it} is the wage offered to hire one unit of labour, P^M_{it} is the materials' price,[8] $C_{it}(\cdot)$ is the function representing the costs for adjusting the non-flexible inputs, and A_{it} is a profitability shock reflecting both productivity (Ω_{it}) and demand shocks ($\mathcal{X}_{it}$).

Adjusting the non-flexible inputs, i.e. capital and labour, entails costs that are captured by the function $C_{it}(\cdot)$. This cost function is firm-time specific, convex and covers both the cases of simultaneous and sequential adjustment of capital and labour. Intuitively, it captures any possible implicit and explicit cost arising from both the input market conditions and any policy affecting the firm's path of optimal input demand. Overall,

[8]Input prices are exogenously given to the firm before any input decision is made in each period.

instead of a particular model of adjustment costs, such as one based on search frictions (Cooper et al., 2007), I use a more general approach that covers any possible type of adjustment cost but is agnostic about the exact source of adjustment frictions.

Firms decide their optimal input demand. This involves the choice for accumulation of capital, hiring/firing of labour and purchase of materials. Decisions are made in a discrete time setting in order to maximize the expected net present value of future cash flows. The Bellman equation of the firm's dynamic programming problem is:

$$\begin{aligned} V_{it}(S_{it}) &= \max_{K_{it+1},L_{it},M_{it}} \Big\{ \Pi_{it}(A_{it}, K_{it}, K_{it+1}, L_{it-1}, L_{it}, M_{it}) + \beta E\big[V_{it+1}(S_{it+1})|\mathcal{I}_{it}\big] \Big\} \\ &= \max_{K_{it+1},L_{it},M_{it}} \Big\{ R_{it}(A_{it}, K_{it}, L_{it}, M_{it}) - P^I_{it} I_{it} - P^L_{it} L_{it} - P^M_{it} M_{it} \\ &\qquad - C_{it}(A_{it}, K_{it}, K_{it+1}, L_{it-1}, L_{it}) + \beta E\big[V_{it+1}(S_{it+1})|\mathcal{I}_{it}\big] \Big\} \end{aligned} \tag{4.2}$$

where $V_{it}(\cdot)$ denotes the maximised value of firm i in period t, $S_{it} = \{A_{it}, K_{it}, L_{it-1}\}$ is the vector of state variables, β is the discount factor and $E[\cdot]$ denotes the expected value conditional on the period's available information. The expectation is taken over the distribution of profitability shocks.

In the case of the flexible input, i.e. material, the model boils down to a static optimization problem since there is no forward looking behaviour. At an interior solution, conditional on the choice of the predetermined and dynamic inputs, the static first order condition (FOC) for material is:

$$\theta^M_{it} \frac{P_{it} Q_{it}}{M_{it}} \left(1 - \frac{1}{\eta_{it}}\right) - P^M_{it} = 0 \tag{4.3}$$

where $\theta^M_{it} = \frac{\partial Q_{it}}{\partial M_{it}} \frac{M_{it}}{Q_{it}}$ is the output elasticity of material and $\eta_{it} = \left|\frac{\partial Q_{it}}{\partial P_{it}} \frac{P_{it}}{Q_{it}}\right|$ is the absolute value of the price elasticity of the firm's residual demand in each period. In this case the marginal revenue product of the flexible input is equal to its marginal cost.

Note that $\mu_{it} = \frac{\eta_{it}}{\eta_{it}-1}$ represents the equilibrium markup which is a function of the demand elasticity perceived by each firm. Alternatively, we can think of the markup as an unrestricted function.[9] Epifani and Gancia (2011) build a general theoretical framework showing that this markup function is general enough to cover the most popular models of

[9] As in De Loecker and Warzynski (2012), we can also consider a cost minimisation instead of a profit maximisation problem for the firm. In this case we abstain from committing to a specific structure for output market.

imperfect competition, such as: Dixit-Stiglitz monopolistic competition with a continuum of varieties; Dixit-Stiglitz monopolistic competition with a discrete number of varieties; Cournot competition with homogenous products; monopolistic competition with translog demand by Feenstra (2003); the generalization of Dixit-Stiglitz preferences by Benassy (1998); Melitz and Ottaviano (2008); and models of price competition using the 'ideal variety' approach (Salop, 1979; Epifani and Gancia, 2006). In their working paper, Epifani and Gancia (2009) discuss this convenient representation of the markup function and show the specific forms that it takes in some of the above cases.

The FOC for capital combined with the relevant envelope condition gives:

$$\begin{aligned}\beta E\left[\theta^K_{it+1}\frac{P_{it+1}Q_{it+1}}{K_{it+1}}\left(1-\frac{1}{\eta_{it+1}}\right)+(1-\delta_{it})P^I_{it+1}\right]-P^I_{it} \leq \frac{\partial C_{it}(A_{it},K_{it},K_{it+1},L_{it-1},L_{it})}{\partial K_{it+1}}\\ +\beta E\left[\frac{\partial C_{it+1}(A_{it+1},K_{it+1},K_{it+2},L_{it},L_{it+1})}{\partial K_{it+1}}\right]\end{aligned} \tag{4.4}$$

where, on the right hand side of the equation, the first component is the marginal cost of adjusting new capital, and the second component is the cost advantage of adjusting capital tomorrow from adjusting capital today. Therefore, the right hand side captures the contribution of the adjustment costs to optimal investment policy. It is clear that the presence of costs for adjusting capital generates a wedge between the expected marginal revenue product and the marginal cost of capital. Alternatively, it can be seen as the difference between the direct and shadow price of capital.

Similarly, for the case of labour:

$$\begin{aligned}\theta^L_{it}\frac{P_{it}Q_{it}}{L_{it}}\left(1-\frac{1}{\eta_{it}}\right)-P^L_{it} \leq &\frac{\partial C_{it}(A_{it},K_{it},K_{it+1},L_{it-1},L_{it})}{\partial L_{it}}\\ &+\beta E\left[\frac{\partial C_{it+1}(A_{it+1},K_{it+1},K_{it+2},L_{it},L_{it+1})}{\partial L_{it}}\right]\end{aligned} \tag{4.5}$$

where the right hand side of the equation captures the marginal costs of adjusting labour. As in the case of capital, the costs for adjusting labour drive a wedge between the marginal revenue product and marginal cost of labour. Equivalently, this wedge can be seen as the difference between the wage of workers and their shadow wage.

Both expressions (4.4) and (4.5) hold with inequality because of the possibility of corner solutions, i.e. non-adjusting firms. On the one hand, when firms adjust both capital and labour expressions hold with equality. On the other hand, when at least one of the inputs does not adjust expressions hold with inequality. The inequality shows that, at any other attainable level of the input that is not adjusted, the marginal cost of adjusting is not equal to the marginal benefit.

Overall, in both expressions, adjustment costs drive a wedge between the marginal revenue product and marginal cost for each of the non-flexible inputs. This is represented on the right hand side of (4.4) and (4.5). In this case, the wedge captures any existing friction in the relevant input market that does not allow firms to freely adjust their input.

Given that the exact nature of the adjustment costs and thus their functional form are unknown, I cannot estimate the wedge from the right hand side of expression (4.4) and (4.5), respectively. However, from the left hand side I can express this wedge as a function of variables observed in the data and estimatable parameters of the production function. It is important to mention that in the case of firms not adjusting to at least one of the non-flexible inputs, these effects will be captured at a lower bound ($\leq$).

After rearranging (4.4), I express firm-level capital market frictions (henceforth KMF) as:

$$KMF_{it}(\theta_{it}^{K}, \beta, \delta_{it}) = \left| \theta_{it}^{K} \frac{P_{it}Q_{it}}{P_{it}^{I}K_{it}} \left(1 - \frac{1}{\eta_{it}}\right) + (1 - \delta_{it}) - \frac{P_{it-1}^{I}}{\beta P_{it}^{I}} \right| \tag{4.6}$$

Because of the time it takes for the aspect of capital to adjust, the firm can only fully observe the benefits and costs from adjusting capital in the period that the new capital becomes productive. This is because there are ongoing costs and benefits between the period that the new capital is chosen ($t-1$) and the period it becomes productive (t). Since the choice for capital was made in the previous period, I also need to give a premium to the past period's values and thus divide all terms with the discount factor β. To correct for the fact that the gap is measured in monetary values, I divide (4.4) by P_{it}^{I}. As such, the expression represents the share of the marginal costs of adjustment by the direct cost of new capital. The absolute value symmetrically treats both the case of investing and divesting.

Rearranging (4.5), I express firm-level labour market frictions (henceforth LMF) as:

$$LMF_{it}(\theta_{it}^{L}) = \left| \theta_{it}^{L} \frac{P_{it}Q_{it}}{P_{it}^{L}L_{it}} \left(1 - \frac{1}{\eta_{it}}\right) - 1 \right| \tag{4.7}$$

Since labour adjusts within the period, the direct costs and benefits of labour are observed by the firm during this period. Similar to capital, I express the wedge as a share of the per-period average wage of the firm, P_{it}^{L}. The absolute value treats the gaps from net hires and fires symmetrically.

Overall, I have constructed statistics that measure the presence of frictions in the labour and capital market. These are uniteless firm-level measures expressed as functions of variables retrieved from the data and parameters of the production function to be estimated. They are inherently relative measures and are interpreted as follows: firms with larger values of KMF_{it} (LMF_{it}) face relatively more frictions in the capital (labor) market.[10] Both measures are expected to capture any type of frictions present in the capital and labour market.

4.3 Empirical Methodology

The effects of KMF and LMF on firm productivity are estimated by introducing the relevant measures of frictions into a—typical in the literature—production function estimation procedure. This section serves as an overview of the steps followed and assumptions made. For a detailed description see Appendix 4.B.

I consider a flexible gross-output production function:

$$Y_{it} = F(K_{it}, L_{it}, M_{it})\mathrm{e}^{\omega_{it}+\epsilon_{it}} \tag{4.8}$$

where

$$\mathrm{e}^{\omega_{it}} = \Omega_{it} \tag{4.9}$$

with Hicks-neutral total factor productivity (TFP) ω_{it}. In logs, it takes the following form:

[10]Petrin and Sivadasan (2006, 2013) consider a similar measure of economic inefficiency for the special case of firing costs, but keep it in monetary units.

$$y_{it} = f(k_{it}, l_{it}, m_{it}) + \omega_{it} + \epsilon_{it} \tag{4.10}$$

where y_{it}, k_{it}, m_{it} are log values of deflated (at the industry-level) operating revenue, tangible fixed assets and material costs, respectively. l_{it} is the log of the total number of employees for firm i at time t. TFP is unobserved to the econometrician but known to the firm. Ex-post shocks, i.e. after the firm's decision about its input use, are picked up by ϵ_{it} and are mean independent of all variables known to the firm in t, i.e. $E[\epsilon_{it}|\mathcal{I}_{it}] = E[\epsilon_{it}] = 0$.

The estimation of the production function is based on the flexible parametric estimator proposed by Gandhi, Navarro, and Rivers (2016). On top of the transmission bias, i.e. firms observing their TFP when choosing their inputs, this estimator controls for the value-added bias, i.e. estimating a value-added rather than a gross-output production function.[11] Appendix 4.B outlines the assumptions and steps followed.

For the core part of the analysis, I consider the classic environment of perfect competition in both input and output markets. As aforementioned, capital is a pre-determined input and therefore chosen one period prior to the realisation of TFP. Frictions in the labour market induce high labour adjustment costs, however, firms still manage to adjust their labour within the period. Therefore, labour is a dynamic input that is relatively more flexible than capital since it is chosen during the TFP realisation. The only flexible input in the specification is material, assumed to freely adjust in each period (variable) and have no dynamic implications (static).

In line with proxy variable methods, this procedure follows two-steps and allows to both estimate the production function technology and identify the potential effects of KMF and LMF on future TFP. From the first step, I can express TFP as a function of the estimatable vector of parameters α of the production function technology $f(\cdot)$, i.e. $\omega_{it}(\alpha)$. I proceed in the second step by exploiting the assumption over the law of motion of TFP. I assume that ω_{it} evolves over time according to the following stochastic process:

$$\omega_{it} = E[\omega_{it}|\mathcal{I}_{it-1}] + \xi_{it} \tag{4.11}$$

[11] See Gandhi et al. (2016) for an exposition of the sizeable effects of value-added bias on TFP heterogeneity. In Chapter 3, my co-author and I show the impact of such a misspecification when estimating learning by doing effects.

where ξ_{it} captures, unanticipated at $t-1$, exogenous shocks that affect the firm's TFP in t, i.e. $E[\xi_{it}|\mathcal{I}_{it-1}] = 0$. Similar to the seminal work of Olley and Pakes (1996), an exogenous first order Markov process can be assumed, i.e. $\omega_{it} = E[\omega_{it}|\omega_{it-1}] + \xi_{it}$. However, exogeneity should be relaxed in order to accommodate the fact that TFP evolves endogenously in response to the firm's actions. This has been shown for the case of R&D by Aw et al. (2008, 2011) and Doraszelski and Jaumandreu (2013); the case of importing by Kasahara and Rodrigue (2008); the case of exporting by De Loecker (2013); and the case of changes in the firm's operating environment, i.e. removing trade barriers, by De Loecker (2011). Taking this into account, I use the case of a controlled Markov process in (4.11), so as to explicitly allow for certain elements of $\mathcal{I}_{it-1}$ to affect TFP. For the baseline specification of the application, the expectation of TFP conditional on the information at $t-1$ is:

$$\omega_{it} = g(\omega_{it-1}, kmf_{it-1}, lmf_{it-1}) + \rho_t + \rho_j + \rho_r + \rho_c + \xi_{it} \tag{4.12}$$

where, on top of lagged TFP, lagged observable variables for firm i in period t are also allowed to affect current TFP outcomes (in expectation)[12]: kmf_{it-1} and lmf_{it-1} are the log of the measure of frictions in the capital and labour market, respectively, ρ_t, ρ_j, ρ_r, and ρ_c are relevant fixed effects that account for macroeconomic shocks and aggregate structural differences between countries, industries and regions, respectively.[13]

I can now express the 'innovation' of TFP (ξ_{it}) as a function of the production function parameters by regressing $\omega_{it}(\alpha)$ on $g\big(\omega_{it-1}(\alpha), kmf_{it-1}(\alpha), lmf_{it-1}(\alpha)\big)$ and the relevant fixed effects. Note that, as in the case of TFP, our variables of interest $kmf_{it-1}(\alpha)$ and $lmf_{it-1}(\alpha)$ are expressed as functions of the estimatable parameters of the production function. This is because their respective output elasticities $\theta^K_{it}(\alpha)$ and $\theta^L_{it}(\alpha)$ are also functions of the α's. Specifically, the log of the measures of KMF and LMF used in the

[12] With lagged values, I inherently assume that it takes one period for actions to affect TFP. Such an assumption can be relaxed and tested for robustness against alternative specifications with additional lags. For the estimations, I use both a linear ($\omega_{it} = \rho_\omega \omega_{it-1} + \rho_\kappa kmf_{it-1} + \rho_\lambda lmf_{it-1} + \rho_t + \rho_j + \rho_r + \rho_c + \xi_{it}$) and second order polynomial ($\omega_{it} = \rho_\omega \omega_{it-1} + \rho_\kappa kmf_{it-1} + \rho_\lambda lmf_{it-1} + \rho_{\omega\omega}\omega^2_{it-1} + \rho_{\kappa\kappa} kmf^2_{it-1} + \rho_{\lambda\lambda} lmf^2_{it-1} + \rho_{\omega\kappa}\omega_{it-1} kmf_{it-1} + \rho_{\omega\lambda}\omega_{it-1} lmf_{it-1} + \rho_{\kappa\lambda} kmf_{it-1} lmf_{it-1} + \rho_{\omega\kappa\lambda}\omega_{it-1} kmf_{it-1} lmf_{it-1} + \rho_t + \rho_j + \rho_r + \rho_c + \xi_{it}$) approximation of $g(\cdot)$. Fixed effects enter additively in order to restrict the parameter space and improve the efficiency of the estimation.

[13] More specifically, $\rho_t, \rho_j, \rho_r, \rho_c$ capture time, industry (if estimated at the sectoral level), nuts2-region (if estimated at the industry or sectoral level) and country (if estimated at the EU level) fixed effects, respectively.

estimations are expressed as:

$$kmf_{it}(\alpha, \delta_j) = ln\left|\theta_{it}^{K}(\alpha)\frac{P_{it}\widehat{Y}_{it}}{P_{it}^{I}K_{it}} - \delta_j\right| \tag{4.13}$$

$$lmf_{it}(\alpha) = ln\left|\theta_{it}^{L}(\alpha)\frac{P_{it}\widehat{Y}_{it}}{P_{it}^{L}L_{it}} - 1\right| \tag{4.14}$$

where $\widehat{Y}_{it} = \frac{Y_{it}}{e^{\widehat{\epsilon}_{it}}}$ is the observed output (Y_{it}) corrected[14] for the estimated - from the first step - ex-post shocks to production ($\widehat{\epsilon}_{it}$), $P_{it}^{I}K_{it}$ is the cost of physical capital, $P_{it}^{L}L_{it}$ is the cost of labour and $P_{it}Y_{it}$ is total sales.[15]

The second step proceeds with an iterative Generalised Method of Moments (GMM). To estimate the parameters of interest, I form a GMM criterion function based on the following moment conditions:

$$E\big[\xi_{it}(\alpha) \otimes \mathcal{Z}_{\nu}'\big] = 0 \tag{4.15}$$

where $\mathcal{Z}_{\nu} = \left(k_{it}, l_{it-1}, \ldots, k_{it}^{\nu_k} l_{it-1}^{\nu_l}\right)$ is the - typical in the literature - 'instrument matrix' with its column space dimension depending on the degree ν of the polynomial used to approximate the production function. The orthogonality conditions depend on the timing assumptions of inputs. Capital is predetermined and thus orthogonal to the innovation of TFP. However, I rely on lagged values for labour since current labour is expected to be correlated with TFP and therefore $E\big[\xi_{it}(\alpha)l_{it}\big] \neq 0$.

By minimising the sample analogue of (4.15), I retrieve estimates for the parameters of the production function technology (α). Within this step, I can also directly estimate the effects on future TFP from LMF $\left(\frac{\partial g(\cdot)}{\partial lmf_{it-1}}\right)$ and KMF $\left(\frac{\partial g(\cdot)}{\partial kmf_{it-1}}\right)$.

[14] This is a necessary correction since potential inhomogeneities in the data can severely distort the magnitudes of the measures. For the same reason, special attention is paid to how I trim the data.

[15] For both measures, since I assume that firms operate under perfect competition in the output market, $\eta_{it} \to \infty \Rightarrow \left(1 - \frac{1}{\eta_{it}}\right) = 1$. For the measure of capital market frictions, since I do not observe the direct price of investment, P_{it}, I make the simplifying assumption that when the choice for capital is made, its price is approximately equal to its next period's discounted price, i.e. $P_{it-1}^{I} \approx \beta P_{it}^{I}$. Finally, the depreciation rate of capital, δ_j, is directly computed from the data as the total amount of depreciation and amortization of the assets over total assets. I use total instead of fixed assets since the numerator contains depreciation of both intangibles, other assets and amortization. To avoid outliers I trim the top and bottom percentile of their distribution.

4.4 Data

I use a firm-level panel of manufacturing firms from 16 EU countries[16] for the period 2002-2007. The datasource is the Amadeus database by Bureau van Dijk Electronic Publishing (2011) (BvDEP). BvDEP regularly updates the information set in Amadeus and releases a monthly DVD containing the latest information on ownership. Firms that exit the market are dropped fairly rapidly. For a complete set of financial and ownership information over time, I use a time series of (annual) DVDs to construct a consistent database. This allows me to build a dataset with nearly full financial and administrative information i.e. balance sheet, profit and loss account, activities, location, ownership, exit and entry. Merlevede et al. (2015) describe the construction and representativeness of the data at length.

I focus on the sample of active manufacturing[17] firms that file unconsolidated accounts.[18] I retain firms reporting operating revenue, tangible fixed assets, number of employees, costs of employees, material inputs, NACE 2-digit level industry classification, NUTS 2-digit region classification, date of incorporation, and ownership information.[19] I remove outliers using the BACON method proposed by Billor et al. (2000).[20] Firms re-entering are removed from the sample, as are firms with less than two years of data. This results in an unbalanced panel of 146268 firms and 992047 observations for 16 EU countries for the period 2002-2007 (see Table 4.C.2 in Appendix).

All monetary variables are deflated using the appropriate country-NACE Rev.2 2-digit output deflator from the EU KLEMS database. (Real) *Output* (Y), is operating revenue turnover deflated with producer price indices. *Capital* (K), is tangible fixed assets deflated by the average of the deflators of various NACE Rev.2 2-digit industries (Javorcik, 2004b).[21] (Real) *Material* (M), is material inputs deflated by an intermediate

[16]This includes Belgium (BE), Bulgaria (BG), Czech Republic (CZ), Germany (DE), Estonia (EE), Spain (ES), Finland (FI), France (FR), Croatia (HR), Italy (IT), Norway (NO), Poland (PL), Romania (RO), Sweden (SE), Slovenia (SI) and Slovakia (SK).

[17]Table 4.C.1 in Appendix 4.C provides an overview of the NACE Rev.1.1 2-digit industries included.

[18]Accounts not integrating the statements of controlled subsidiaries or branches of the concerned company.

[19]For HR I also have information on exporting statues of the firm.

[20]BACON stands for Block Adaptive Computationally efficient Outlier Nominators. It is a multiple outlier detection method. The variables considered in the method are log of output, labour, capital and material. The procedure is applied each time at the level of the estimation, i.e. industry-country, country, industry-EU or EU specific.

[21]Electrical equipment (27); machinery and equipment n.e.c. (28); motor vehicles, trailers and semi-trailers (29); and other transport equipment (30).

input deflator constructed as a weighted average of output deflators, where country-time-industry specific weights are based on intermediate input uses retrieved from input-output tables. *Labour* (L), is the number of employees. 'Firm' wage (W) is measured as the cost of employees to the number of employees. Table 4.C.2 shows summary statistics for the firms in the sample.

4.5 Results

In this section, I first report the basic results of labour and capital market frictions on TFP using the approach described in Section 4.3(Tables 4.1 and 4.2). Finally, in Table 4.3, I present the TFP effects when input market frictions interact with exporting.

4.5.1 TFP Effects from Labour and Capital Market Frictions

Table 4.1 reports the TFP effects from labour market frictions. Each line refers to a separate estimation at the industry level including all 16 EU countries. The first column reports the average estimated effect for a linear approximation of equation (4.12), while the last four columns report the average, 25th, 50th and 75th percentiles, respectively, from the distribution of estimated effect when considering a second order polynomial approximation.

An increase in labour market frictions (LMF) leads to a significant and positive increase in future TFP for the majority of industries. Since higher market rigidities translate to higher labour adjustment costs, firms need to utilise their existing labour force in a more efficient and costless way to meet demand for their output. Possible mechanisms include improvements in management practices and organisational forms, i.e. intrinsic motivation.

Organisational performance is a function of both intrinsic and extrinsic motivation. On the one hand, intrinsic motivation is difficult to induce and its outcome is hard to assess due to uncertainty. Therefore, organisations prefer to extrinsically motivate their employees via a reward and command system (Argyris, 2001). On the other hand, transfer of tacit knowledge, creativity and multi-tasking are closely related to intrinsic motivation (Osterloh and Frey, 2000). As such, managers need to compare the benefits and costs associated to each type of motivation.

Table 4.1: TFP effects from LMF in EU

Industry	Linear	General - 2nd order			
	Mean	p(25)	Mean	Median	p(75)
15	0.003***	0.002***	0.005***	0.005***	0.008***
17	0.002*	-0.001	0.003***	0.004***	0.008***
18	-0.003	-0.012***	-0.006	-0.007	0.001
19	0.002	0.004	0.008	0.008	0.012***
20	0.004***	0.003***	0.005***	0.005***	0.006***
21	0.005***	0.003**	0.007***	0.007***	0.010***
22	0.009**	0.010	0.012**	0.013**	0.015***
24	0.009***	0.009***	0.012***	0.012***	0.015***
25	0.003	0.003***	0.005***	0.005***	0.006***
26	0.020***	0.003***	0.006***	0.006***	0.009***
27	0.002	-0.000	0.002	0.003	0.005
28	0.009	0.003	0.004	0.004	0.006
29	0.005***	0.004***	0.007***	0.007***	0.010***
31	0.004***	0.003***	0.007***	0.007***	0.010***
32	0.011***	0.006*	0.008***	0.008**	0.010***
33	0.007	0.004	0.008	0.008	0.011**
34	0.001	-0.000	0.001	0.002	0.003
35	0.002	-0.002	0.001	0.001	0.004
36	0.008***	0.007***	0.009***	0.010***	0.012***
37	0.013***	-0.003	0.006	0.006	0.016**

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Linear and General-2nd order refers to a linear and 2nd order polynomial approximation of $g(\cdot)$, respectively. Both specifications include additive year and country fixed effects. This table reports the marginal effects $\frac{\partial \omega_{it}}{\partial lmf_{it-1}}$ from each specification, estimated for each Nace Rev1.1 2-digit industry in the sample. For the latter specification I report different moments of the distribution of estimated effects. Standard errors are block-bootstrapped with 500 replications over the GNR two-step estimation procedure and are not reported for space considerations.

labour.

In Table 4.1, I report the TFP effects from capital market frictions using the same estimation methodology as above. I observe that an increase in capital market frictions (KMF) leads to a significant and positive increase in future TFP. In periods of increased capital market frictions it is very costly for firms to replace or update their existing capital. Therefore, they have to come up with costless ways of reconfiguring their existing capital in order to make their production processes more efficient to meet demand.

Table 4.2: TFP effects from KMF in EU

Industry	Linear	General - 2nd order			
	Mean	p(25)	Mean	Median	p(75)
15	0.004***	-0.002*	0.002	0.002*	0.005***
17	0.005***	-0.004**	0.005***	0.005***	0.014***
18	-0.005**	-0.021***	-0.012***	-0.012***	-0.002
19	0.001	0.002	0.006	0.007	0.011
20	0.008***	0.000	0.003*	0.004**	0.007***
21	0.003*	-0.001	0.002	0.002	0.005**
22	0.003***	0.001	0.001	0.001	0.002
24	0.011***	0.005**	0.007***	0.007***	0.010***
25	0.002**	-0.004***	-0.000	-0.001	0.003***
26	0.008***	-0.003	0.002	0.003*	0.009***
27	0.006***	-0.002	0.003	0.003	0.008
28	0.004***	0.002	0.003**	0.003***	0.004***
29	0.011	0.004***	0.008***	0.008***	0.012***
31	0.010	0.003	0.009***	0.009***	0.016***
32	0.002	-0.001	0.003	0.003	0.007**
33	0.007	0.000	0.004	0.004	0.007
34	0.006***	-0.001	0.003	0.004	0.008
35	0.005	-0.007**	-0.001	-0.001	0.005*
36	0.012***	0.004	0.009***	0.010***	0.014***
37	0.003	-0.003	0.000	-0.000	0.004

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Linear and General-2nd order refers to a linear and 2nd order polynomial approximation of $g(\cdot)$, respectively. Both specifications include additive year and country fixed effects. This table reports the marginal effects $\frac{\partial \omega_{it}}{\partial kmf_{it-1}}$ from each specification, estimated for each Nace Rev1.1 2-digit industry in the sample. For the latter specification I report different moments of the distribution of estimated effects. Standard errors are block-bootstrapped with 500 replications over the GNR two-step estimation procedure and are not reported for space considerations.

As before, intrinsic motivation of employees is a non-monetary mechanism that results in creative ideas for reconfiguring capital. However, productivity improvements via this channel are less prevalent compared to the case of labour. This is reconciled by the fact that capital adjusts less freely than labour, as it is a tangible fixed asset. This is particularly true in the manufacturing sector: production lines face capacity constraints that are mainly relaxed when firms undertake new investments (e.g. new machineries or upgrading production processes) while labour can be managed more flexibly.[22]

4.5.2 TFP Effects from LMF, KMF and Trade

In this section I interact labour and capital market frictions with the exporting status of the firm, i.e. exp_{it-1}.[23] From Table 4.3, I see that labour market frictions are in line with the results presented above, while increased capital market frictions negatively affect future TFP. Firms in Croatia's developing economy can only increase their future TFP over time once they face less frictions in the capital market. This implies that it is less costly to adjust new capital that will in turn improve their production lines and performance. Continuing, I observe a typical learning by exporting effect where a firm's performance improves after entering export markets as in De Loecker (2013).[24]

The future TFP of exporters increases by less than that of non-exporters when faced with increased labour market frictions. Openness makes firms more willing to incur the costs associated with adjusting their workforce (Coşar et al., 2016). Therefore, compared to non-exporters, they are less likely to intrinsically motivate their existing workforce thus increasing their future TFP less than non-exporters. Interacting capital market frictions with firms' exporting status yields a negative but statistically insignificant effect, pointing again to the non-flexible to adjust nature of capital. On average, both exporting and non-exporting firms are equally constrained from capital market frictions.

[22]For the Manufacture of wearing apparel and dressing and dyeing of fur I find a negative impact of capital market frictions on future TFP, suggesting that firms increase their future TFP once capital market frictions are reduced via the introduction of new production processes that reduce x-inefficiencies and also allow labour to be more productive.

[23]Since information for exporting status is limited only to HR, I restrict the analysis to this country.

[24]In this case the average learning by exporting effect is 0.5% and it is considerably smaller compared to that estimated in the literature so far (De Loecker, 2013; Manjón et al., 2013; Fernandes and Isgut, 2015). The driving force for this discrepancy is that in most cases the production function estimation procedure followed do not correct for the value-added bias discussed in Chapter 3.

Table 4.3: TFP effects from input market frictions and trade in HR

	p(25)	Average	Median	p(75)
ω_{it-1}	0.753***	0.822***	0.822***	0.890***
	(0.019)	(0.014)	(0.019)	(0.027)
lmf_{it-1}	-0.001	0.007***	0.006***	0.012***
	(0.002)	(0.001)	(0.002)	(0.002)
kmf_{it-1}	-0.004***	-0.002**	-0.002**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
exp_{it-1}	-0.001	0.005*	0.008***	0.013***
	(0.003)	(0.003)	(0.003)	(0.004)
$lmf_{it-1} * exp_{it-1}$	-0.009***	-0.005*	-0.006**	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)
$kmf_{it-1} * exp_{it-1}$	-0.003	-0.000	-0.001	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	7305	7305	7305	7305

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Estimates are a second order polynomial approximation of the specification $g(\omega_{it-1}, lmf_{it-1}, kmf_{it-1}, exp_{it-1})$. I report different moments of the distribution of estimated results. All specifications include additive year, industry and region fixed effects. Standard errors are block-bootstrapped with 500 replications over the GNR two-step estimation procedure and are reported in parentheses below point estimates.

4.6 Conclusion

In this paper I treat frictions in the labour and capital market as a possible source of future TFP improvements via learning mechanisms. Using a novel approach, I find that increases in labour market frictions positively affect the future TFP of firms. This is in line with the idea that, during periods of increased rigidities in the labour market, firms face higher costs for adjusting labour. Therefore, they are forced to find alternative costless channels to substitute the costly adjustment of labour in order to meet demand for their final output. Such channels include improving management and organisational practices, e.g. intrinsic motivation. Overall, the increase in future TFP of firms comes from the more efficient use of costless intangible inputs due to the slow or non-adjustment of tangible inputs, i.e. labour.

Nonetheless, increases in capital market frictions do induce significant TFP effects but are less prevalent and significant compared to the case of labour market frictions. In periods of increased capital market frictions it is very costly for firms to replace or update their existing capital. Therefore, they have to come up with costless ways to reconfigure their existing capital in order to make their production processes more productive to meet demand. However, TFP improvements via this channel are less prevalent compared to the case of labour. This is reconciled with the less-flexible-to-adjust nature of capital (tangible fixed assets) versus labour, especially in the manufacturing sector. Indeed, manufacturing production lines face capacity constraints that can mainly be relaxed when firms undertake new investments (i.e. new machineries or upgrade of production processes), while labour can be managed more flexibly.

Overall, I provide suggestive evidence that firms are able to exploit any possible flexibility in their structures (non-monetary mechanisms) in order to substitute alternative choices (adjusting labour) that are relatively more costly during certain periods. The higher the levels of flexibility, i.e. reassigning tasks across the existing workforce, the higher the future TFP effects. This effect is not uniform and is more prevalent in non-trading firms that are less likely to incur costs.

Concluding, the results should be considered as a special case from the broader set of mechanisms induced from input market frictions that could affect firm's efficiency. This is important to bare in mind when assessing policy reforms on the labour and capital market.

Appendix 4.A A Model of Adjusting Factors

I describe in detail the elements of the model and any assumptions made. The model is in line with the estimation procedure used in the next section. Any significant remarks and extensions are introduced vis-a-vis the model description.

4.A.1 Production Function

A single-product firm i at time t produces a nonstorable[25] output using the following production technology:

$$Q_{it}^S = F_{it}^S(K_{it}, L_{it}, M_{it}, \Omega_{it}) \tag{4.16}$$

where K_{it} is the capital level, L_{it} is the stock of homogeneous workers, M_{it} is the materials level, Ω_{it} is the firm's productivity and $F_{it}^S(\cdot)$ is the production technology used by firm i in period t.[26]

4.A.2 Demand

Firms face a downward sloping demand curve:

$$Q_{it}^D = F_{it}^D(P_{it}, \mathcal{X}_{it}) \tag{4.17}$$

where P_{it} is the output price level and $\mathcal{X}_{it}$ is a stochastic demand shock. Therefore, the inverse residual demand function $P_{it}(Y_{it}, \mathcal{X}_{it})$ will depend both on its output and the demand shifter respectively. By not imposing any further restrictions on consumer preferences, I allow for firm-time specific price elasticities of demand that in combination with various (static) price setting models allow for firm-time specific markups as in De Loecker and Warzynski (2012).

[25] Both for simplicity and lack of data, I assume that inventories do not serve as a source of adjustment.

[26] The choice of inputs used in the production process directly depends on the data in hand. Upon access to relevant information the model can be extended to allow for heterogeneity in employment (e.g. high-skilled vs low-skilled or temporary vs permanent workers), materials (e.g. outsource vs offshore) and additional inputs (e.g. energy consumption and hours worked) as in Doraszelski and Jaumandreu (2014).

4.A.3 Revenue Function

With equilibrium in the output market, $Q_{it} = Q_{it}^S = Q_{it}^D$, I get the firm's revenue function:

$$R_{it}(A_{it}, K_{it}, L_{it}, M_{it}) = P_{it}(Q_{it}, \mathcal{X}_{it}) * Q_{it} \tag{4.18}$$

where $A_{it} = \{\mathcal{X}_{it}, \Omega_{it}\}$ includes both the shocks to demand and productivity respectively.[27]

4.A.4 Costs

Firms face two types of costs. First, is the direct cost of obtaining each input used in the production process:

$$DC_{it} = P_{it}^I I_{it} + P_{it}^L L_{it} + P_{it}^M M_{it} \tag{4.19}$$

where P_{it}^I is the direct purchase price of new capital,[28] P_{it}^L is the wage offered to hire one unit of employment and P_{it}^M is the material price. All input prices are exogenously set and known to the firm before any input decision is made in each period.

Second, is the cost of adjusting the non-flexible inputs, in this case capital and labour:

$$C_{it}(A_{it}, K_{it}, K_{it+1}, L_{it-1}, L_{it}) = \begin{cases} C_{it}^K(A_{it}, K_{it}, K_{it+1}) & , if I_{it} \neq 0 \\ C_{it}^L(A_{it}, L_{it-1}, L_{it}) & , if \Delta L_{it} \neq 0 \\ C_{it}^{KL}(A_{it}, K_{it}, K_{it+1}, L_{it-1}, L_{it}) & , if \Delta L_{it} * I_{it} \neq 0 \end{cases} \tag{4.20}$$

where $C_{it}^K(\cdot)$ captures any type of convex cost embedded in the adjustment process of capital (i.e. invest, $I_{it} > 0$, or divest, $I_{it} < 0$). This includes: installation costs (time and

[27] In the special case of CES preferences, $Q_{it}^D = \left(\frac{P_{it}}{\mathcal{X}_{it}}\right)^\sigma$, where the price elasticity of demand (σ) is constant for all firms, and under a Cobb-Douglas production function, $Q_{it}^S = {K_{it}}^{a_k} {L_{it}}^{a_l} {M_{it}}^{a_m} A_{it}$, the revenue function boils down to $R_{it} = A_{it}({K_{it}}^{a_k} {L_{it}}^{a_l} {M_{it}}^{a_m})^{\left(1+\frac{1}{\sigma}\right)}$, where $A_{it} = \mathcal{X}_{it} {\Omega_{it}}^{\left(1+\frac{1}{\sigma}\right)}$ is revenue productivity as in Klette and Griliches (1996).

[28] I allow the price of capital to take different values, $P_{it}^I = \{P_{it}^{I^s}, P_{it}^{I^b}\}$, when the firm sells (divest) or buys (invest) capital, respectively. This implies that capital is not fully reversible due to transactions costs, physical costs of resale and the market for lemons phenomenon (Abel and Eberly, 1998; Sakellaris, 2004; Contreras, 2008). The main implications of irreversibility were originally analyzed by Arrow (1968); Lucas and Prescott (1971); Nickell (1974). More recent investment models with irreversibility include Bertola and Caballero (1990); Pindyck (1991); Dixit (1992); Abel and Eberly (1994); Bertola and Caballero (1994); Dixit and Pindyck (1994). For a review of the analytical and empirical literature on irreversible investment and evidence on its macro implications see Servén (1997).

resources); learning of new technologies; disruption of productive activities; reallocation of resources; reassignment of tasks; reconfiguration of the production process; indivisibilities in capital; access to finance; changes in the extent of subsidies to new investment in capital equipment; etc.

The cost function $C_{it}^{L}(\cdot)$ captures all convex costs that the firm faces when adjusting labour (i.e. hiring, $\Delta L_{it} > 0$, or firing, $\Delta L_{it} < 0$). This includes: severance pay; disruptions to production from reassignment of workers; search costs; training costs; fees to replacement agencies; mandatory advanced notice of layoffs; overhead cost of maintaining a human resource department; etc.

The component $C_{it}^{KL}(\cdot)$ captures any convex cost related to adjusting capital and labour simultaneously. This includes both of the prementioned costs from adjusting capital and labour separately, but also costs incurred from adjusting them at the same time. Such costs could be positive (complementarity in the simultaneous adjustment of capital and labour) or negative (cost advantage from sequential adjustment of each input). For example, a firm may hire workers while investing in a new technology in order to install the new capital and bring it to full productivity faster than otherwise. However, some firms prefer to employ new workers and buy new machinery separately since the costs associated with new workers learning a new technology include higher fixed costs and longer adjustment periods than otherwise.

The adjustment cost function $C_{it}(\cdot)$ is firm-time specific, imposes no restrictions on the form of convex components and covers both the cases of simultaneous and sequential adjustment of capital and labour. Therefore, it includes any possible implicit and explicit cost that arises from both the conditions in the input market and any policies affecting the firm's path of optimal input demand. Overall, instead of a specific model of adjustment costs, e.g. search frictions (Cooper et al., 2007), I employ a more general approach that covers any possible type of adjustment costs, but is agnostic about the exact sources of adjustment frictions in play.

It is important to mention here that the adjustment cost is treated as a function of K_{it}, K_{it+1}, since capital is a pre-determined input and L_{it-1}, L_{it}, since labour is a dynamic input that adjusts within the period. If I now assume that labour is also pre-determined I just need to update the relevant components for the cost function to L_{it}, L_{it+1} since labour chosen today becomes productive in the next period.

Combining all sources of costs for the firm, I get the following cost function:

$$TC_{it} = P^I_{it} I_{it} + P^L_{it} L_{it} + P^M_{it} M_{it} + C_{it}(A_{it}, K_{it}, K_{it+1}, L_{it-1}, L_{it}) \tag{4.21}$$

4.A.5 A Note on Non-convex Adjustment Costs

Early attempts of the literature, employed standard neoclassical investment models with convex adjustment costs in order to understand aggregate investment activity (Hall and Jorgenson, 1969; Tobin, 1969). However, even at the aggregate level, such models have not performed well (Caballero, 1999). Aggregate statistics mask important underlying dynamics, since they smooth over various types of capital accumulation patterns across firms. A growing number of firm-level studies suggest a non-smooth adjustment path for the capital stock due to the intermittent and lumpy nature of investment.[29] Such studies emphasise the importance of non-convex adjustment costs on understanding the dynamics of capital adjustment.[30]

In the same spirit, although aggregate series are smooth, employment adjustment at the plant-level is extremely lumpy (Hamermesh, 1989; Davis and Haltiwanger, 1992). Labour adjustment distribution has fat tails, mix of small and large adjustments and a mass point around the inaction region.[31] Strand of the literature has focused on non-convex adjustment costs as a source of this heterogeneity. More specifically, they focus on the importance of non-convexities in adjustment costs for explaining plant level observations.[32] Their findings indicate that non-convex adjustment costs are critical for explaining plant-level patterns employment (hours) adjustment and aggregate behaviour

[29] See Caballero et al. (1995); Doms and Dunne (1998); Nilsen and Schiantarelli (2003) and Sakellaris (2004).

[30] Seminal contributions on the non-convex nature of adjustment costs include the discussion of Rothschild (1971) and evidence from industry case studies for specific technologies by Holt et al. (1960) and Peck (1974). Note that the theoretical literature had always been well ahead of its empirical counterpart on how to accommodate these issues since access to firm-level data came at a later point in time. Relevant studies include Rust (1987); Cooper and Haltiwanger (1993); Abel and Eberly (1994); Caballero et al. (1995); Caballero and Leahy (1996); Cooper et al. (1999); Caballero and Engel (1999); Cooper and Haltiwanger (2006) and Letterie and Pfann (2007). For a review of such models see Adda and Cooper (2003) and Bond and Van Reenen (2007).

[31] For micro-level studies on patterns of labour adjustment, see Hamermesh (1989); Davis and Haltiwanger (1992); Caballero et al. (1995, 1997) and Davis et al. (1998).

[32] See Hamermesh (1989); Caballero and Engel (1993); Caballero et al. (1997); Aguirregabiria and Alonso-Borrego (2014) and Cooper et al. (2015).

(Cooper and Willis, 2004, 2009).[33]

In the prementioned literature, the focus is in the adjustment of only one quasi-fixed production input. However, recent empirical evidence shows that firms adjust along several margins and that the dynamics of capital and labour demand are interrelated.[34] The results indicate that models with fully specified interrelated non-convex adjustment cost structures outperform all other specifications.[35] Therefore, it is important to consider the additional costs from adjusting inputs simultaneously.

However, in this paper I consider convex adjustment costs that lead to analytical solutions. In order to accommodate the possibility of periods of non-adjustment and abstract from non-convexities in the adjustment cost function I can directly extend the model by pushing the optimal programme forward until the firm adjusts again, as in Pakes (1994). For an application on a model with only firing costs see Petrin and Sivadasan (2006).

4.A.6 Profit Function

Subtracting costs from revenues, I compute the firm's profit function:

$$\begin{aligned}\Pi_{it}(A_{it}, K_{it}, K_{it+1}, L_{it-1}, L_{it}, M_{it}) =& R_{it}(A_{it}, K_{it}, L_{it}, M_{it}) - P^I_{it} I_{it} - P^L_{it} L_{it} - P^M_{it} M_{it} \\ & - C_{it}(A_{it}, K_{it}, K_{it+1}, L_{it-1}, L_{it})\end{aligned} \tag{4.22}$$

4.A.7 Adjustment and Timing of Inputs

The periodical information set of the firm is denoted by $\mathcal{I}_{it}$ and includes any type of information that the firm uses to make its period input decisions. Capital is assumed to be a predetermined input and thus in the firm's information set upon use in the period's production process, i.e. $\{K_{i0t}\} \in \mathcal{I}_{it}$. The choice for new capital is made in $t-1$ while it

[33]For a lengthy discussion on models of labour adjustment see Hamermesh (1996) and Bond and Van Reenen (2007), and for detailed research on the nature of labour adjustment costs see Hamermesh and Pfann (1996); Abowd and Kramarz (2003); Rota (2004); Nilsen et al. (2007) and Kramarz and Michaud (2010).

[34]For non-structural approaches using micro-level data see Sakellaris (2004); Letterie et al. (2004) and Nilsen et al. (2009). For models with joint adjustment of capital and labour see Shapiro (1986); Galeotti and Schiantarelli (1991); Abel and Eberly (1998); Hall (2004); Merz and Yashiv (2007); Bloom (2009).

[35]See Contreras (2008); Lapatinas (2012) and Asphjell et al. (2014).

only becomes productive in t (time to adjust new capital) and faces adjustment costs.[36] Capital accumulates, with probability one, according to $K_{it} = (1 - \delta_{it})K_{it-1} + I_{it-1}$, where δ_{it} is the rate of capital depreciation and I_{it-1} is the investment in new capital.

Labour is assumed to be a dynamic input, meaning that it is variable in period t, i.e. $L_{i0t} \notin \mathcal{I}_{it}$, and has dynamic implications, i.e. $\frac{\partial}{\partial L_{i0t-1}} L_{i0t} \neq 0$, due to the presence of adjustment costs. Labour is 'more flexible' than capital, since it is both chosen and becomes productive within t (no whole period to adjust labour) but also faces adjustment costs.[37] Labour evolves, with probability one, according to the law of motion $L_{it} = L_{it-1} + \Delta L_{it}$, where ΔL_{it} refers to the net changes in employment.[38]

The only flexible input is material, which is variable in each period, i.e. $M_{i0t} \notin \mathcal{I}_{it}$, and has no dynamic implications, i.e. $\frac{\partial}{\partial M_{i0t-1}} M_{i0t} = 0$.[39]

4.A.8 Firm's Decision Problem

Firms decide the optimal demand for inputs to be used in their production process.[40] This involves the choice for accumulation of capital (choosing I_{it} is equivalent to choosing K_{it+1}), hiring/firing labour and purchase of material inputs.[41]

The firm decides in a discrete time setting in order to maximize the expected net present value of future cash flows. The Bellman equation of the firm's dynamic programming

[36] Adjustment costs inherently capture the costs associated with the time to adjust new capital, i.e. disruption of production.

[37] This assumption represents the fact that it is easier and takes less time to adjust labour relative to capital. However, there are countries or markets where firms face a very stringent labour market environment and therefore need a period to adjust their labour, as considered in Konings and Vanormelingen (2015). For an extensive discussion of various cases on the timing of inputs see Ackerberg et al. (2006).

[38] I inherently assume that there are no simultaneous hiring and firing decisions, i.e. gross changes. This translates to hiring when $\Delta L_{it} > 0$ and firing when $\Delta L_{it} < 0$. Also, the quit rate for employment is assumed zero due to data restrictions and focus of the paper in the average behaviour of labour. For a detailed discussion on gross and net changes in employment see Hamermesh and Pfann (1996).

[39] Material is assumed to face no adjustment costs or period lag. However, it can be further split between in-house production and outsourced/offshored materials in order to account for contractual relationships between suppliers and firms (Grossman and Helpman, 2002, 2005) that generate possible adjustment costs as in Doraszelski and Jaumandreu (2014).

[40] I implicitly assume that decisions are made by managers and there are no incentive problems between the manager and the owners of the firm. Therefore, managers always maximise the value of the firm though optimal input decisions.

[41] Without any loss of generality the model can be extended to any type of input that the firm owns, hires, rents or purchases in order to accommodate the production process in each period.

problem is:

$$\begin{aligned} V_{it}(S_{it}) &= \max_{K_{it+1},L_{it},M_{it}} \Big\{ \Pi_{it}(\Omega_{it}, K_{it}, K_{it+1}, L_{it-1}, L_{it}, M_{it}) + \beta E\big[V_{it+1}(S_{it+1})|\mathcal{J}_{it}\big] \Big\} \\ &= \max_{K_{it+1},L_{it},M_{it}} \Big\{ R_{it}(\Omega_{it}, K_{it}, L_{it}, M_{it}) - P^I_{it} I_{it} - P^L_{it} L_{it} - P^M_{it} M_{it} \\ &\qquad - C_{it}(\Omega_{it}, K_{it}, K_{it+1}, L_{it-1}, L_{it}) + \beta E\big[V_{it+1}(S_{it+1})|\mathcal{J}_{it}\big] \Big\} \end{aligned} \tag{4.23}$$

where $V_{it}(\cdot)$ denotes the maximised value of firm i in period t, $S_{it} = \{A_{it}, K_{it}, L_{it-1}\}$ is the vector of state variables, β is the discount factor and $E[\cdot]$ denotes the expected value conditional on the period's available information. The expectation is taken over the distribution of profitability shocks.[42]

In the case of the flexible input, i.e. material, the model boils down to a static optimization problem since there is no forward looking behaviour. At an interior solution, conditional on the choice of predetermined and dynamic inputs, the static first order condition (FOC) for material is:

$$\theta^M_{it} \frac{P_{it} Q_{it}}{M_{it}} \left(1 - \frac{1}{\eta_{it}}\right) - P^M_{it} = 0 \tag{4.24}$$

where $\theta^M_{it} = \frac{\partial Q_{it}}{\partial M_{it}} \frac{M_{it}}{Q_{it}}$ is the output elasticity of material and $\eta_{it} = \left| \frac{\partial Q_{it}}{\partial P_{it}} \frac{P_{it}}{Q_{it}} \right|$ is the absolute value of the price elasticity of the firm's residual demand in each period.[43] In this case the marginal revenue product of the flexible input is equal to its marginal cost.

4.A.8.1 No Adjustment Costs

In order to understand the contribution of adjustment costs I start from the benchmark case where adjustment costs are absent, i.e. $C_{it}(\Omega_{it}, K_{it}, K_{it+1}, L_{it-1}, L_{it}) \equiv 0$ for all $\Omega_{it}, K_{it}, K_{it+1}, L_{it-1}$ and L_{it}. Note that the accumulation of capital remains forward looking, i.e. time to adjust aspect of capital. The FOC for capital combined with the

[42] The uncertainty about the future arises because A_{it} evolves probabilistically. I assume that the profitability shocks evolve probabilistically following a first order Markov process. Note that the distribution of future productivity depends not only on current productivity but also on other possible factors (e.g. frictions in the labour or capital market and exporting status) that are key components of the estimation strategy.

[43] Note that the markup of firm i at time t is captured by $\mu_{it} = \frac{\eta_{it}}{\eta_{it}-1}$. In the limit case of perfect competition where products are perfect substitutes, $\eta_{it} \to \infty$ and therefore $\mu_{it} = 1$.

respective envelope condition gives:

$$\beta E\left[\theta^K_{it+1}\frac{P_{it+1}Q_{it+1}}{K_{it+1}}\left(1-\frac{1}{\eta_{it+1}}\right)+(1-\delta_{it})P^I_{it+1}\right]-P^I_{it}=0 \tag{4.25}$$

where $\theta^K_{it+1}=\frac{\partial Q_{it+1}}{\partial K_{it+1}}\frac{K_{it+1}}{Q_{it+1}}$ is the output elasticity of capital for firm i in period $t+1$. The expected marginal return on capital is equated with the cost of an additional unit of capital today. The first term in brackets refers to the marginal profits from capital and the second term captures the resale value of non-depreciated capital at the next period's price (P^I_{it+1}).

Similar to the case of materials, the FOC for labour will come from the static per-period maximisation solution:

$$\theta^L_{it}\frac{P_{it}Q_{it}}{L_{it}}\left(1-\frac{1}{\eta_{it}}\right)-P^L_{it}=0 \tag{4.26}$$

where $\theta^L_{it}=\frac{\partial Q_{it}}{\partial L_{it}}\frac{L_{it}}{Q_{it}}$ is the output elasticity of labour for firm i in period $t+1$.[44]

4.A.8.2 With Adjustment Costs for Capital and Labour

The FOC for capital combined with the relevant envelope condition gives:

$$\begin{aligned}\beta E\left[\theta^K_{it+1}\frac{P_{it+1}Q_{it+1}}{K_{it+1}}\left(1-\frac{1}{\eta_{it+1}}\right)+(1-\delta_{it})P^I_{it+1}\right]-P^I_{it} &\leq \frac{\partial C_{it}(\Omega_{it},K_{it},K_{it+1},L_{it-1},L_{it})}{\partial K_{it+1}}\\ &+\beta E\left[\frac{\partial C_{it+1}(\Omega_{it+1},K_{it+1},K_{it+2},L_{it},L_{it+1})}{\partial K_{it+1}}\right]\end{aligned} \tag{4.27}$$

where the first component of the right hand side of the inequality is the marginal cost of adjusting new capital and the second component is the cost advantage on adjusting capital tomorrow from adjusting capital today. Therefore, the right hand side captures the contribution of the adjustment costs on optimal investment policy. It is clear that the presence of adjustment costs generates a wedge between the expected marginal revenue product and the marginal cost of new capital. Alternatively, it can be seen as the difference

[44] In the case where labour needs one period to adjust, the firm has to choose today the labour that will become productive next period (L_{it+1}). Therefore, the FOC becomes $\beta E\Big[\theta^L_{it+1}\frac{P_{it+1}Q_{it+1}}{L_{it+1}}\left(1-\frac{1}{\eta_{it+1}}\right)-P^L_{it+1}\Big]=0$. This is similar to the expression for capital (4.25), but without the extra term on the right hand side, since labour is chosen every period and is not like capital that is accounted by the firm as a cumulative asset that depreciates and can be liquidated next period.

between the direct and shadow price of capital.

Similarly, for the case of labour:

$$\theta_{it}^{L}\frac{P_{it}Q_{it}}{L_{it}}\left(1-\frac{1}{\eta_{it}}\right)-P_{it}^{L}\leq\frac{\partial C_{it}(\Omega_{it},K_{it},K_{it+1},L_{it-1},L_{it})}{\partial L_{it}}+\beta E\left[\frac{\partial C_{it+1}(\Omega_{it+1},K_{it+1},K_{it+2},L_{it},L_{it+1})}{\partial L_{it}}\right] \tag{4.28}$$

where the right hand side of the inequality captures the marginal costs of adjusting labour. As before, the costs for adjusting labour drive a wedge between the marginal revenue product and marginal cost of labour. Equivalently this wedge is the difference between the wage of workers and their shadow wage.[45]

Both expressions hold with inequality because of the possibility of corner solutions, i.e. non-adjusting firms. On the one hand, when firms adjust both capital and labour expressions hold with equality.[46]On the other hand, when at least one of the inputs does not adjust, expressions hold with inequality. The inequality shows that at any other attainable level of the input that is not adjusted, the marginal cost of adjusting is not equal to the marginal benefit.[47]

Overall, I see in both expressions that adjustment costs drive a wedge between the marginal revenue product and marginal cost of the non-flexible inputs. Compared to the cases of no adjustment costs, (4.25) and (4.26), this wedge is represented in the right hand side of (4.27) and (4.28). In this case, the wedge captures any possible friction in labour and capital markets that do not allow firms to freely adjust their inputs.

4.A.8.3 Measures of Capital and Labour Market Frictions

Given that I do not know the exact nature of adjustment costs and therefore their functional form, I cannot estimate this wedge from the right hand-side of expressions (4.27) and (4.28). However, from the left hand side I can express this wedge as a function

[45]In the case of time to adjust labour, (4.28) becomes $\beta E\left[\theta_{it+1}^{L}\frac{P_{it+1}Q_{it+1}}{L_{it+1}}\left(1-\frac{1}{\eta_{it+1}}\right)-P_{it+1}^{L}\right]\leq\frac{\partial C_{it}(\Omega_{it},K_{it},K_{it+1},L_{it},L_{it+1})}{\partial L_{it+1}}+\beta E\left[\frac{\partial C_{it+1}(\Omega_{it+1},K_{it+1},K_{it+2},L_{it+1},L_{it+2})}{\partial L_{it+1}}\right]$.

[46]This produces typical Euler equations (interior solutions) where inputs adjust smoothly every period under the assumption of convex adjustment costs. This allows for analytically solvable models which in investment theory are labelled as Q-model. For a detailed overview see Adda and Cooper (2003) and Bond and Van Reenen (2007).

[47]This highly non-convex nature in the decision rules is generated by the introduction of adjustment costs allowing for simultaneous and sequential adjustment of capital and labour.

of variables retrieved from the data and parameters to be estimated. It is important to mention that in the case of firms not adjusting at least one of the non-flexible inputs, these effects will be captured at a lower bound ($\leq$).

After rearranging (4.27), I express frictions in the capital market as:

$$KMF_{it}(\theta_{it}^{K}, \beta, \delta_{it}) = \left| \theta_{it}^{K} \frac{P_{it}Q_{it}}{P_{it}^{I}K_{it}} \left(1 - \frac{1}{\eta_{it}}\right) + (1 - \delta_{it}) - \frac{P_{it-1}^{I}}{\beta P_{it}^{I}} \right| \tag{4.29}$$

Because of the time to adjust aspect of capital, the firm will fully observe the benefits and costs from adjusting capital only in the period that the new capital becomes productive. This is because there are costs and benefits that evolve between the period that the new capital is chosen $(t-1)$ and the period it becomes productive (t). Since the choice for capital was made in the previous period, I also need to give a premium to the past period's values and thus divide all terms with the discount factor β. To control for the fact that the gap is measured in monetary values I divide (4.27) with P_{it}^{I}. This way the expression represents the share of marginal costs of adjustment over the direct cost of new capital. The absolute value allows me to include in one measure both the cases of firms investing or divesting.[48] KMF is a uniteless measure of frictions in the capital market that is a function of variables retrieved from the data and parameters to be estimated.

After rearranging (4.28), I express frictions in labour market as:

$$LMF_{it}(\theta_{it}^{L}) = \left| \theta_{it}^{L} \frac{P_{it}Q_{it}}{P_{it}^{L}L_{it}} \left(1 - \frac{1}{\eta_{it}}\right) - 1 \right| \tag{4.30}$$

Since labour adjusts within the period, the direct costs and benefits of labour are observed by the firm in this period. Similar to the case of capital, I express the gap as a share of the per-period average wage P_{it}^{L}.[49] The absolute value treats symmetrically the gaps from net hires and fires. LMF it is a uniteless measure of frictions in the labour market that is expressed as a function of variables retrieved from the data and parameters to be

[48]This implies that I inherently assume symmetry in the adjustment cost function for investing and divesting. Further heterogeneity can be uncovered by allowing asymmetry in the measures. However, I abstain from that since I am interested in the average behaviour of the firm and specifically the Euclidean distance of the gap from 0. Also, it prevents the parameter space of our estimation routine from growing exponentially and resulting in a computationally intensive estimation.

[49]In the case of time to adjust labour, (4.30) remains the same but is generated from the expression in footnote 45, following the same steps as in the case of capital.

estimated.

Overall, I structurally back-out statistics that measure the presence of frictions in the labour and capital market. These are uniteless firm-specific measures that are expressed as functions of variables retrieved from the data and parameters to be estimated. They are inherently relative measures interpreted as: firms with larger values of KMF_{it} (LMF_{it}) face relatively more frictions in the capital (labour) market, i.e. more stringent. As prementioned this measure includes all types of frictions that are present in the capital and labour market and also the way that each firm experiences them in each period.

Appendix 4.B GNR Estimation Procedure

This section describes the steps and assumptions needed to estimate the effects of LMF and KMF on future TFP within a GNR two-step production function estimation procedure. For an in-depth analysis of the production function estimation procedure refer to Gandhi et al. (2016).

This case considers the classic environment of perfect competition in both input and output markets. Conditional on the state variables and other firm characteristics, the firm's static profit maximisation problem yields the first order condition with respect to the flexible input, material:

$$P_t^M = P_t \frac{\partial}{\partial M_{it}} F(K_{it}, L_{it}, M_{it}) \mathrm{e}^{\omega_{it}} \mathcal{E} \tag{4.31}$$

where P_t^M and P_t is the price of material and output respectively. Under perfect competition in input and output markets, they are constant across firms within the same industry but can vary across time. By the time firms make their periodic decisions, ex-post shock ϵ_{it} is not in their information set. Hence, firms create expectations over it that are similar across firms, $\mathcal{E} = E(\mathrm{e}^{\epsilon_{it}})$.[50]It is important to account and correct for this term since ignoring it, i.e. $\mathcal{E} = 1$, inherently implies that I move from the mean to the median central tendency of $\mathrm{e}^{\epsilon_{it}}$ (see Goldberger, 1968).

Combining (4.31) with production function (4.10) and re-arranging terms, I retrieve a share equation:

$$s_{it} = ln\ G(K_{it}, L_{it}, M_{it}) + ln\mathcal{E} - \epsilon_{it} \tag{4.32}$$

where s_{it} is the log of the nominal share of intermediate inputs and $G(K_{it}, L_{it}, M_{it}) = \frac{\partial lnF^S(K_{it},L_{it},M_{it})}{\partial lnM_{it}}$ is the output elasticity of the flexible input, material. Note that the share equation is net of the productivity term ω_{it}, inducing the transmission bias.

[50]I inherently assume that the existence of any measurement error is symmetric across firms and thus does not affect the results.

4.B.1 Step One

A Non Linear Least Squares (NLLS) estimation of the share equation (4.32) is applied, with:

$$G(L_{it}, K_{it}, M_{it})\mathcal{E} = \sum_{r_k+r_l+r_m\leq r} \gamma'_{r_k,r_l,r_m} k_{it}^{r_k} l_{it}^{r_l} m_{it}^{r_m},\ with\ \ r_k, r_l, r_m \geq 0 \tag{4.33}$$

approximated by a polynomial series estimator of order r. From this optimisation routine I identify $\widehat{\epsilon}_{it}$ (hence $\widehat{\mathcal{E}}$) and the parameters $\widehat{\gamma'}_{r_k,r_l,r_m}$. I recover $\widehat{\gamma}_{r_k,r_l,r_m} \equiv \frac{\widehat{\gamma'}_{r_k,r_l,r_m}}{\widehat{\mathcal{E}}}$, $\forall\ r_k, r_l, r_m$ and compute the output elasticity of the flexible input material $\widehat{G}(\cdot)$.[51]

4.B.2 Step Two

By integrating up the output elasticity of the flexible input:

$$\int \frac{G(K_{it}, L_{it}, M_{it})}{M_{it}} dM_{it} = lnF(K_{it}, L_{it}, M_{it}) + \mathcal{B}(K_{it}, L_{it}) \tag{4.34}$$

I identify the production function up to an unknown constant of integration.[52] By differencing it with the production function (4.10) I retrieve the following equation for productivity:

$$\omega_{it} = \mathcal{Y}_{it} + \mathcal{B}(K_{it}, L_{it}) \tag{4.35}$$

where $\mathcal{Y}_{it}$ is the log of the expected output net of the computed integral (4.34) and $\mathcal{B}(K_{it}, L_{it})$ is the constant of integration, approximated by a polynomial series estimator of degree ν:[53]

$$\mathcal{B}(K_{it}, L_{it}) = \sum_{\nu_k+\nu_l\leq\nu} \alpha_{\nu_k,\nu_l} k_{it}^{\nu_k} l_{it}^{\nu_l},\ with\ \ \nu_k, \nu_l > 0 \tag{4.36}$$

[51]For the estimations I employ a polynomial of order $r = 2$, $\widehat{G}(\cdot) = \widehat{\gamma}_0 + \widehat{\gamma}_k k_{it} + \widehat{\gamma}_l l_{it} + \widehat{\gamma}_m m_{it} + \widehat{\gamma}_{kk} k_{it}^2 + \widehat{\gamma}_{ll} l_{it}^2 + \widehat{\gamma}_{mm} m_{it}^2 + \widehat{\gamma}_{kl} k_{it} l_{it} + \widehat{\gamma}_{km} k_{it} m_{it} + \widehat{\gamma}_{lm} l_{it} m_{it} + \widehat{\gamma}_{klm} k_{it} l_{it} m_{it}$. Note that I also include the triplet of capital, labour and materials to account for possible interactions between them. I abstain from using polynomials of higher order since estimation becomes computationally intensive but results are similar.

[52]Because of the polynomial sieve estimator chosen above, the integral has a closed-form solution: $\int \frac{G(K_{it},L_{it},M_{it})}{M_{it}} dM_{it} = \sum_{r_k+r_l+r_m\leq r} \frac{\gamma_{r_k,r_l,r_m}}{r_m+1} k_{it}^{r_k} l_{it}^{r_l} m_{it}^{r_m+1},\ with\ \ r_k, r_l, r_m \geq 0$.

[53]For the estimations I employ a polynomial of order $\nu = 2$, $\mathcal{B}(\cdot) = \alpha_k k_{it} + \alpha_l l_{it} + \alpha_{kk} k_{it}^2 + \alpha_{ll} l_{it}^2 + \alpha_{kl} k_{it} l_{it}$. I abstain from using polynomials of higher order since estimation becomes computationally intensive but results are similar.

Therefore after the first stage, I can express productivity as:

$$\omega_{it}(\alpha) = \widehat{\mathcal{Y}}_{it} + \sum_{\nu_k+\nu_l \leq \nu} \alpha_{\nu_k,\nu_l} k_{it}^{\nu_k} l_{it}^{\nu_l}, \ \forall\ \alpha = \{\alpha_{\nu_k,\nu_l} \forall \nu_k, \nu_l\} \tag{4.37}$$

To proceed, I exploit the assumption over the law of motion of productivity. Similar to the seminal work of Olley and Pakes (1996), an exogenous first order Markov process can be assumed, $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$. However, exogeneity should be relaxed in order to accommodate the fact that TFP evolves endogenously in response to the affiliate's actions. This has been shown for the case of R&D by Aw et al. (2008) and Doraszelski and Jaumandreu (2013); the case of importing by Kasahara and Rodrigue (2008); the case of exporting by De Loecker (2013); and the case of changes in firms' operating environment, i.e. removing trade barriers, by De Loecker (2011). Therefore, the law of motion for productivity should be modified so as to explicitly allow for certain elements of $\mathcal{I}_{t-1}$ to affect TFP.

On top of lagged productivity, lagged and observable variables for firm i in period t are also allowed to affect current productivity outcomes (in expectation):[54]

$$\omega_{it} = g(\omega_{it-1}, kmf_{it-1}, lmf_{it-1}, s_{it-1}) + \rho_t + \rho_j + \rho_r + \rho_c + \xi_{it} \tag{4.38}$$

kmf_{it-1} and lmf_{it-1} are the log of the measure of frictions in the capital and labour market, respectively, ρ_t, ρ_j, ρ_r, and ρ_c are relevant fixed effects that account for macroeconomic shocks and aggregate structural differences between countries, industries and regions, respectively.[55] and ξ_{it} denotes the productivity innovation.[56]

I can now express the 'innovation' of TFP $\xi_{it}(\alpha)$ as a function of the parameters of the constant of integral, by regressing $\omega_{it}(\alpha)$ on $g(\omega_{it-1}(\alpha), kmf_{it-1}(\alpha), lmf_{it-1}(\alpha), s_{it-1})$. Note that, as in the case of current and lagged TFP, the measures of capital and labour

[54] By employing lagged values I inherently assume that it takes one period for actions to affect productivity.

[55] More specifically $\rho_t, \rho_j, \rho_r, \rho_c$ capture time, industry (if estimated at the sectoral level), nuts2-region (if estimated at the industry or sectoral level) and country (if estimated at the EU level) fixed effects, respectively.

[56] For the estimations, I use both a linear ($\omega_{it} = \rho_\omega \omega_{it-1} + \rho_\kappa kmf_{it-1} + \rho_\lambda lmf_{it-1} + s_{it-1} + \xi_{it}$) and second order polynomial ($\omega_{it} = \rho_\omega \omega_{it-1} + \rho_\kappa kmf_{it-1} + \rho_\lambda lmf_{it-1} + \rho_{\omega\omega}\omega_{it-1}^2 + \rho_{\kappa\kappa} kmf_{it-1}^2 + \rho_{\lambda\lambda} lmf_{it-1}^2 + \rho_{\omega\kappa}\omega_{it-1} kmf_{it-1} + \rho_{\omega\lambda}\omega_{it-1} lmf_{it-1} + \rho_{\kappa\lambda} kmf_{it-1} lmf_{it-1} + \rho_{\omega\kappa\lambda}\omega_{it-1} kmf_{it-1} lmf_{it-1} + s_{it-1} + \xi_{it}$) approximation of $g(\cdot)$ with additive fixed effects s_{it-1}. Fixed effects enter additively in order to restrict the parameter space and improve the efficiency of the estimation. I abstain from reporting third order polynomials since results are similar and the estimation becomes computationally intensive.

market frictions are expressed as functions of the parameters of the constant of integral, since their respective output elasticities are also functions of α's:

$$\begin{aligned}\theta_{it}^{K}(\alpha) &= \frac{\partial lnF(K_{it}, L_{it}, M_{it})}{\partial lnK_{it}} = \frac{\partial \int \frac{\widehat{G}(K_{it},L_{it},M_{it})}{M_{it}} dM_{it}}{\partial lnK_{it}} - \frac{\partial \mathcal{B}(K_{it}, L_{it})}{\partial lnK_{it}} \\ &= \sum_{r_k+r_l+r_m \leq r} \frac{\widehat{\gamma}_{r_k,r_l,r_m}}{r_m+1} r_k k_{it}^{r_k-1} l_{it}^{r_l} m_{it}^{r_m+1} - \sum_{\nu_k+\nu_l \leq \nu} \alpha_{\nu_k,\nu_l} \nu_k k_{it}^{\nu_k-1} l_{it}^{\nu_l}\end{aligned} \tag{4.39}$$

$$\begin{aligned}\theta_{it}^{L}(\alpha) &= \frac{\partial lnF(K_{it}, L_{it}, M_{it})}{\partial lnL_{it}} = \frac{\partial \int \frac{\widehat{G}(K_{it},L_{it},M_{it})}{M_{it}} dM_{it}}{\partial lnL_{it}} - \frac{\partial \mathcal{B}(K_{it}, L_{it})}{\partial lnL_{it}} \\ &= \sum_{r_k+r_l+r_m \leq r} \frac{\widehat{\gamma}_{r_k,r_l,r_m}}{r_m+1} r_l k_{it}^{r_k} l_{it}^{r_l-1} m_{it}^{r_m+1} - \sum_{\nu_k+\nu_l \leq \nu} \alpha_{\nu_k,\nu_l} \nu_l k_{it}^{\nu_k} l_{it}^{\nu_l-1}\end{aligned} \tag{4.40}$$

Specifically, the log of the measures of capital and labour market frictions employed in the estimations are expressed as:[57]

$$kmf_{it}(\alpha, \delta_j) = ln\left|\theta_{it}^{K}(\alpha)\frac{P_{it}\widehat{Y}_{it}}{P_{it}^{I}K_{it}} - \delta_j\right| \tag{4.41}$$

$$lmf_{it}(\alpha) = ln\left|\theta_{it}^{L}(\alpha)\frac{P_{it}\widehat{Y}_{it}}{P_{it}^{L}L_{it}} - 1\right| \tag{4.42}$$

where $\widehat{Y}_{it} = \frac{Y_{it}}{e^{\widehat{\epsilon}_{it}}}$, is the observed output (Y_{it}) corrected for the estimated - from the first step - ex-post shocks to production ($\widehat{\epsilon}_{it}$) , $P_{it}^{I}K_{it}$ is the cost of physical capital, $P_{it}^{L}L_{it}$ is the cost of labour and $P_{it}Y_{it}$ is total sales.

The second step proceeds with an iterative Generalised Method of Moments (GMM) technique. The set of moments used are $E\left[\xi_{it}(\alpha) \otimes n'_{it}\right] = 0$, where $n_{it} = (k_{it}, l_{it-1}, k_{it}l_{it-1}, \cdots, k_{it}^{\nu_k} l_{it-1}^{\nu_l}) \;\forall\; \nu$ $0 \mid \nu_k + \nu_l \leq \nu$.[58] The orthogonality conditions, directly depend on the timing assumptions of inputs. Capital is assumed to be decided a period ahead and therefore orthogonal to the innovation in productivity. However, for labour I rely on lagged values since current labour is expected to react to shocks to productivity, and therefore $E\left[\xi_{it}(\alpha) l_{it}\right]$ is expected

[57] For the estimations I employ a polynomial of order $r = 2$ for $G(\cdot)$ and $\nu = 2$ for $\mathcal{B}(\cdot)$. Hence, the respective output elasticities become: $\theta_{it}^{K}(\alpha) = (\widehat{\gamma}_k + 2\widehat{\gamma}_{kk}k_{it} + \widehat{\gamma}_{kl}l_{it} + \frac{\widehat{\gamma}_{km}}{2}m_{it} + \frac{\widehat{\gamma}_{klm}}{2}l_{it}m_{it})m_{it} - \alpha_k - 2\alpha_{kk}k_{it} - \alpha_{kl}l_{it}$ and $\theta_{it}^{L}(\alpha) = (\widehat{\gamma}_l + 2\widehat{\gamma}_{ll}l_{it} + \widehat{\gamma}_{kl}k_{it} + \frac{\widehat{\gamma}_{lm}}{2}m_{it} + \frac{\widehat{\gamma}_{klm}}{2}k_{it}m_{it})m_{it} - \alpha_l - 2\alpha_{ll}l_{it} - \alpha_{kl}k_{it}$.

[58] For the estimations I use a polynomial of degree $\nu = 2$ for $\mathcal{B}(\cdot)$ leading to $n_{it} = (k_{it}, l_{it-1}, k_{it}^2, l_{it-1}^2, k_{it}l_{it-1})$.

to be nonzero.[59]

On the one hand, from this two-step procedure, I retrieve estimates of the production function coefficients that allow us to compute productivity $\hat{\omega}_{it}$ and other relevant variables, i.e. output elasticities of inputs and returns to scale for firm i at time t, using the following form of gross-output production function:[60]

$$y_{it} = \sum_{r_k+r_l+r_m \leq r} \frac{\widehat{\gamma}_{r_k,r_l,r_m}}{r_m+1} k_{it}^{r_k} l_{it}^{r_l} m_{it}^{r_m+1} - \sum_{\nu_k+\nu_l \leq \nu} \widehat{\alpha}_{\nu_k,\nu_l} k_{it}^{\nu_k} l_{it}^{\nu_l} + \omega_{it} + \widehat{\epsilon}_{it} \tag{4.43}$$

On the other hand, the effects on future productivity of firms from labour $\frac{\partial g(\cdot)}{\partial lmf_{it-1}}$ and capital $\frac{\partial g(\cdot)}{\partial kmf_{it-1}}$ market frictions can directly be estimated within the second step. This means that by exploiting the optimal decisions from the dynamic problem of a firm I can capture frictions in the capital and labour market as a function of parameters that can directly be identified within any typical semi-parametric model.

[59] In the case of time to adjust aspect of labour, the moment condition should include current instead of lagged labour.

[60] For the estimations I employ a polynomial of order $r = 2$ for $G(\cdot)$ and $\nu = 2$ for $\mathcal{B}(\cdot)$. Hence, $y_{it} = (\gamma_0 + \gamma_k k_{it} + \gamma_l l_{it} + \frac{\gamma_m}{2} m_{it} + \gamma_{kk} k_{it}^2 + \gamma_{ll} l_{it}^2 + \frac{\gamma_{mm}}{3} m_{it}^2 + \gamma_{kl} k_{it} l_{it} + \frac{\gamma_{km}}{2} k_{it} m_{it} + \frac{\gamma_{lm}}{2} l_{it} m_{it} + \frac{\gamma_{klm}}{2} k_{it} l_{it} m_{it}) m_{it} - \alpha_l l_{it} - \alpha_k k_{it} - \alpha_{ll} l_{it}^2 - \alpha_{kk} k_{it}^2 + \alpha_{kl} k_{it} l_{it} + \omega_{it} + \epsilon_{it}$.

Appendix 4.C Figures and Tables

Table 4.C.1: List of NACE Rev.1.1 2-digit industries included in the data.

Broad category	NACE 2-digit	Description
DA	15	Manufacture of food products and beverages
DA	16	Manufacture of tobacco products
DB	17	Manufacture of textiles
DB	18	Manufacture of wearing apparel; dressing and dyeing of fur
DC	19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear
DD	20	Manufacture of wood and products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
DE	21	Manufacture of pulp, paper and paper products
DE	22	Publishing, printing and reproduction of recorded media
DF	23	Manufacture of coke, refined petroleum products and nuclear fuel
DG	24	Manufacture of chemicals and chemical products
DH	25	Manufacture of rubber and plastic products
DI	26	Manufacture of other non-metallic mineral products
DJ	27	Manufacture of basic metals
DJ	28	Manufacture of fabricated metal products, exc. machinery/equipment
DK	29	Manufacture of machinery and equipment n.e.c.
DL	30	Manufacture of office machinery and computers
DL	31	Manufacture of electrical machinery and apparatus n.e.c.
DL	32	Manufacture of radio/television/communication equipment/apparatus
DL	33	Manufacture of medical/precision/optical instruments, watches/clocks
DM	34	Manufacture of motor vehicles, trailers and semi-trailers
DM	35	Manufacture of other transport equipment
DN	36	Manufacture of furniture; manufacturing n.e.c.
DN	37	Recycling

Table 4.C.2: Firm-level data

Country	Statistics	Operating Revenue	Tangible Fixed Assets	Number of Employees	Material Costs	Average Wage	Exporting Status	SUB 50%
BE	Mean	57900	6579	133	38157	46234	.	.13
	Sd	427306	29431	360	373743	18040	.	.33
	Obs	23689	23689	23689	23689	23689	0	23689
BG	Mean	5324	2412	164	3512	2305	.	.0012
	Sd	56868	20883	499	50486	3137	.	.035
	Obs	8297	8297	8297	8297	8297	0	8297
CZ	Mean	13205	4030	148	8253	10538	0	.0049
	Sd	84317	26427	457	62822	10288	.	.07
	Obs	30528	30528	30528	30528	30528	1	30528
DE	Mean	83516	13904	298	45469	48197	.	.091
	Sd	245665	60317	748	141422	24660	.	.29
	Obs	9886	9886	9886	9886	9886	0	9886
EE	Mean	1612	486	39	978	6253	.2	.0023
	Sd	4825	2104	108	3098	5009	.4	.048
	Obs	12585	12585	12585	12585	12585	5628	12585
ES	Mean	6741	1453	31	4272	23466	.	.0062
	Sd	105343	16287	170	88292	14469	.	.078
	Obs	332585	332585	332585	332585	332585	0	332585
FI	Mean	8083	1985	40	4441	32278	.	.01
	Sd	47542	17413	128	31025	11246	.	.1
	Obs	24871	24871	24871	24871	24871	0	24871
FR	Mean	13122	1572	57	6314	35305	.49	.014
	Sd	85806	12647	241	49177	14936	.5	.12
	Obs	203420	203420	203420	203420	203420	199008	203420
HR	Mean	2577	1293	45	1700	7432	.39	.0042
	Sd	16534	9639	183	10122	5332	.49	.064
	Obs	8649	8649	8649	8649	8649	8600	8649
IT	Mean	13449	2540	53	7332	32743	.	.018
	Sd	91527	17067	182	65535	26368	.	.13
	Obs	215722	215722	215722	215722	215722	0	215722
NO	Mean	9644	1710	35	5616	43714	.	.0095
	Sd	93316	19497	113	75084	19711	.	.097
	Obs	28804	28804	28804	28804	28804	0	28804
PL	Mean	15762	4196	176	9654	8836	.	.0016
	Sd	69609	16590	325	50194	8495	.	.04
	Obs	18379	18379	18379	18379	18379	0	18379
RO	Mean	2231	795	118	1382	1850	.	.00086
	Sd	25407	6836	334	19449	2423	.	.029
	Obs	17522	17522	17522	17522	17522	0	17522
SE	Mean	5597	1338	28	2341	26634	1	.014
	Sd	36047	10680	99	22748	9427	0	.12
	Obs	42747	42747	42747	42747	42747	14709	42747
SI	Mean	5268	2059	58	2944	15291	.86	.0058
	Sd	23413	11034	188	10910	6894	.35	.076
	Obs	10111	10111	10111	10111	10111	5354	10111
SK	Mean	22421	8752	198	14425	18428	.	.0082
	Sd	151855	69293	590	113377	29787	.	.09
	Obs	4252	4252	4252	4252	4252	0	4252

Notes: Firm-level data from Amadeus dataset for 146268 manufacturing firms from 16 EU countries during 2002 to 2007. Operating Revenue, Tangible Fixed Assets and Material are in thousand Euro.

5

Like Father like Son: Technology Transfers and Productivity Effects from Firm Ownership*

5.1 Introduction

Questions revolving around the meaning of firm ownership have generated a considerable amount of research. On the one hand, the literature suggests that ownership structures accommodate the efficient transfer of tangibles. On the other hand, ownership is seen as facilitating the efficient transfer of intangibles often thought of as "know-how."

The flow of physical goods within ownership groups is concentrated in a small number of large affiliates that are owned by large parent firms, both domestically (Atalay et al., 2014) and internationally (Ramondo et al., 2016; Blanas and Seric, 2017a). This provides suggestive evidence that ownership structures are primarily used to facilitate the efficient

*This chapter is based on a paper co-authored with Bruno Merlevede. We thank participants at the ISGEP Sept. 2016 and CEP International Trade Workshop Jun. 2017 for their comments and suggestions. Special thanks are extended to Sotiris Blanas, Paola Conconi, Jan De Loecker, Ruben Dewitte, Gerdie Everaert, Rebecca Freeman, Paul Frijters, Holger Görg, Stefanie Haller, Joep Konings, Asier Mariscal, Gianmarco Ottaviano, Nina Pavcnik, Veronica Rappoport, Glenn Rayp, David A. Rivers, Peter Schott, Joel Stiebale, Catherine Thomas, Felix Tintelnot and Johannes Van Biesebroeck.

transfer of intangibles. As considered theoretically by Arrow (1975) and Teece (1982), common ownership allows firms to transfer intangible inputs across vertically integrated production units, since the alternative of the market is most likely a non-viable substitute.

Since the transfer of tangibles can only explain a small fraction of ownership structures in the economy, it is important to examine the existence and prevalence of the alternative explanation, i.e. the transfer of intangibles, in depth.[1] However, relevant empirical research to date provides only suggestive evidence of this possibility.[2] Likely, this is due to data restrictions which make it difficult to explicitly measure intangible inputs. In most cases, researchers rely on proxies or incomplete measures, e.g. R&D, royalties paid to parents by affiliates, corporate transferees, etc. To our knowledge, there are no micro-level panel datasets that contain information on the full set of intangibles for both parents and affiliates on top of standard balance sheet information. Such datasets would allow researchers to fully specify the production function of each parent-affiliate pair, and hence quantify any transfers of intangibles.

A notable exception is the work of Bilir and Morales (2016). They show, based on a panel of US parents and foreign affiliate(s) with information on output, inputs and R&D investment, that expected affiliate productivity increases with parent innovation. However, R&D spending captures[3] only a specific subset (i.e. proprietary knowledge) of a broad range of intangibles that are potentially transferred within ownership structures. These include but are not limited to: tacit knowledge; know-how; marketing techniques; managerial practices; and organisational practices. Furthermore, their analysis is silent about domestic ownership structures which, according to our data, represent a relatively larger share of firms which are smaller in size. As such, these firms are also less intensive in R&D spending (OECD, 2017). Finally, it is not possible to infer whether the effect they

[1] The existence of one explanation does not mutually exclude the other. To become productive, transfers of tangibles can also be found vis-à-vis transfers of intangibles, i.e. parental assistance and coordination (Keller and Yeaple, 2013; Blanas and Seric, 2017b).

[2] Atalay et al. (2014) document that, despite the lack of shipments of physical goods within multi-plant firms in the United States, newly vertically integrated affiliates start resembling their parent along production and trade activities. Ramondo et al. (2016) confirm this lack of shipments across affiliates of U.S. multinationals. Arnold and Javorcik (2009) and Guadalupe et al. (2012) find that foreign acquisition of domestic firms leads to improvements in: sales; productivity; investment; wages; employment; and innovation. For further documentation on the existence of international technology transfers within the boundaries of the firm see Branstetter et al. (2006); Keller and Yeaple (2013) and Gumpert (2015).

[3] We use the word 'captures' since, similar to physical investment, R&D investment contributes to the periodic accumulation of an 'intangible' input under an (unobserved) stochastic accumulation process. Therefore, lagged R&D spending is actually a proxy for current proprietary knowledge used in the production of the final output. See Griliches (1998) for an extended discussion on this modelling approach.

estimate comes through the channel of technology transfers, i.e. input in the production function of the affiliate, or is a pure effect on the affiliate's productivity dynamics, i.e. learning. Overall, there is ample space to validate or provide further empirical support to ownership theories arguing that firm boundaries exist in order to facilitate the transfer of intangibles.

In this paper we do so by identifying transfers of intangible inputs and demonstrating how they determine a firm's production technology and the evolution of its productivity. We use a carefully constructed European panel of majority owned parent-affiliate groups with full balance sheet information on both sides for the period 2004-2013 and extend a typical production function estimation procedure. In response to data limitations on intangible inputs, we devise a method to characterise the full set of intangibles transferred between parent and affiliate firms.

Specifically, we exploit information from the balance sheet of the parent to identify its productivity. This parent productivity captures both disembodied technological change (e.g. innate characteristics of workers, know-how, etc.) and any potential intangible inputs used in the production of the final output that are not observed in the data (e.g. management practices, acquired characteristics of workers, innovation, etc.).

On the one hand, as theory suggests, if firm boundaries accommodate the transfer of such inputs, we expect affiliates to tap into and use them in the production of their final output. As such, parent productivity (which is now measurable) is introduced as a 'composite' intangible input in the production function of the affiliate. The extent to which parent productivity contributes to the final output of the affiliate is defined as an intangible technology transfer from the parent to its affiliate. Similar to other tangible inputs, i.e. labour, capital and material, this intangible input is measured as the affiliate's output elasticity of parent productivity. Intuitively, one may think of the impact of having, for example, a corporate transferee at the site of the affiliate.

This modelling approach is similar to Griliches and Mairesse (1999) and Bloom et al. (2016) where a proxy for the stock of knowledge and a score for management practices, respectively, are introduced as inputs in the production function technology of the firm. However, our empirical approach provides, instead of an incomplete proxy, an internally consistent composite measure of intangible inputs transferred within the boundaries of the firm.

On the other hand, transfers of intangible technology are potential determinants of the affiliate's productivity evolution. The mechanism we have in mind is any type of learning, where over time the affiliate absorbs/embodies any technological transfer from the parent that affects its overall productivity level in its own intangible technology. Therefore, our empirical methodology allows for technological transfers from the parent to affect the dynamics of affiliate productivity. Intuitively, one may think of a lasting imprint on the affiliates processes after a corporate transferee has left. The modelling approach we follow is similar to Doraszelski and Jaumandreu (2013), De Loecker (2013), and Bilir and Morales (2016) where firms actively learn and assimilate from their actions or changes in their operating environment.

The following findings emerge. First, we show that the productivity of the parent is a significant intangible input in the affiliate's production technology. In addition, such transfers of intangible technology are important determinants of the affiliate's future productivity. Exploiting richness of the data, we find that domestically owned affiliates experience larger technology transfers from their parents, while foreign owned affiliates benefit more from productivity increases induced by learning mechanisms. Overall, we identify, at the firm level, the importance of productivity transfers from various types of ownership structures and confirm the theoretically based argument that firm boundaries exist to facilitate the transfer of intangibles.

The remainder of this paper is organised as follows: in Section 5.2 we present the empirical methodology. In Section 5.3 we describe the data. Section 5.4 presents the main results from applying the proposed methodology to the relevant data, discusses the importance of cross-border barriers in the flow of intangible inputs within the boundaries of the firm and provides a pseudo-placebo test to support the validity of our methodological approach. Finally, Section 5.5 concludes.

5.2 Empirical Methodology

We extend a typical production function estimation procedure to capture potential technology transfers and productivity effects from parent to affiliate. By exploiting information from the balance sheet of the parent we can identify its productivity. This way we can introduce it both as an 'intangible' input in the production function of the affiliate and as a potential determinant of the affiliate's future productivity. This section describes the empirical model of intangible transfers in majority owned firms.

We consider a set of ownership groups $i = 1, \dots, I$ over periods $t = 1, \dots, T$. In each ownership-group-i, the set of active manufacturing firms in t includes firms indexed by $j = 0, \dots, J$, where $j = 0$ denotes the parent firm that has the majority control of its affiliate(s) $j > 0$. The information set of the firm in t is denoted by $\mathcal{I}_t$ and includes any type of information that the firm uses to make its periodic input decisions.

We consider a flexible gross-output production function for the parent:

$$Y_{i0t} = H(K_{i0t}, L_{i0t}, M_{i0t})\mathrm{e}^{\omega_{i0t}+\epsilon_{i0t}} \tag{5.1}$$

with Hicks-neutral total factor productivity (TFP) ω_{i0t}. In logs, equation (5.1) takes the following form:

$$y_{i0t} = h(k_{i0t}, l_{i0t}, m_{i0t}) + \omega_{i0t} + \epsilon_{i0t} \tag{5.2}$$

where y_{i0t}, k_{i0t} and m_{i0t} are log values of deflated (at the country-industry-year level) operating revenue, tangible fixed assets and material costs, respectively. l_{i0t} is the log of the total number of employees of parent 0 in ownership-group-i at time t. TFP is unobserved to the econometrician but known to the firm. Ex-post shocks, i.e. after the firm's decision about its input use, are picked up by ϵ_{i0t} and are mean independent of all variables known to the parent in t, i.e. $E[\epsilon_{i0t}|\mathcal{I}_t] = E[\epsilon_{i0t}] = 0$.

Capital and labour are predetermined inputs and thus chosen one period prior to the TFP realisation. Specifically, firms have information on these inputs and take them into account in the period's production process $\{l_{i0t}, k_{i0t}\} \in \mathcal{I}_t$. The only flexible input is material that freely adjusts in each period, i.e. $m_{i0t} \notin \mathcal{I}_t$. As such, it has no dynamic implications, i.e. $\frac{\partial}{\partial m_{i0t-1}} m_{i0t} = 0$. We assume that both parent and affiliate firms take output and input prices as given.

It is important to emphasise that TFP is not identical to disembodied technological change, known as the 'Solow Residual' (Solow, 1957). This refers to everything that the firm observes but cannot quantify with scientific objectivity, e.g. innate characteristics of workers, know-how, etc. Instead, TFP also includes the impact of inputs that are quantifiable with scientific objectivity from the firm, but not available in the data for the researcher, e.g. management practices, acquired characteristics of workers, innovation etc.

In this spirit, we consider the production function of the affiliate:

$$Y_{ijt} = F(K_{ijt}, L_{ijt}, M_{ijt})(\Omega_{i0t})^{\beta}\mathrm{e}^{\omega_{ijt}+\epsilon_{ijt}} \tag{5.3}$$

where

$$F(K_{ijt}, L_{ijt}, M_{ijt}) = \left(\tilde{F}(K_{ijt}, L_{ijt}, M_{ijt})\right)^{\eta} \tag{5.4}$$

$$\Omega_{i0t} = \mathrm{e}^{\omega_{i0t}} \tag{5.5}$$

In logs, the production function is of the following form:

$$y_{ijt} = f(k_{ijt}, l_{ijt}, m_{ijt}) + \beta\omega_{i0t} + \omega_{ijt} + \epsilon_{ijt} \tag{5.6}$$

where the affiliate's joint output of capital (k_{ijt}), labour (l_{ijt}) and material (m_{ijt}), expressed in levels from the function $\tilde{F}(\cdot)$, is combined with the parent's TFP according to a Cobb-Douglas technology.[4] The TFP of the parent is now introduced as an input in the affiliate's production technology. All factors captured in the TFP measure of the parent are allowed to shift the production frontier of the affiliate. This is an input assumed to be exogenously given from the parent to its affiliate(s) within the group. Therefore, it is known to the affiliate at the time of making its decisions in period t. Ex-post shocks, i.e. after the firm's decision about its input use, are picked up by ϵ_{ijt} and are mean independent of all variables known to the affiliate in t, i.e. $E[\epsilon_{ijt}|\mathcal{I}_t] = E[\epsilon_{ijt}] = 0$.

Equation (5.6) differs from equation (5.2) by the log-additive term $\beta\omega_{i0t}$ which captures the relative importance of measured parent TFP in the affiliate's production technology. This term allows for the separation of the affiliate's TFP from any technology transfers from the parent. Intuitively we consider it as an 'intangible input' in the production function of the affiliate. Therefore, the parameter β measures affiliate-j's output elasticity of its parent-0's TFP.

[4]We allow for general substitution effects by not restricting the elasticity of substitution between the flexible function of capital, labour and materials, and the parent's TFP. Note that the parent's TFP could be readily introduced along the other inputs in the flexible production technology. However, since we are interested in the average behaviour of the firm we believe that the proposed specification suffices.

From equation (5.2), it is apparent that we implicitly assume no 'backward' technology transfers, i.e. no technology transfers from affiliates to their parents. This translates to a technologically 'superior' parent that transfers part of its technology to its affiliate(s), but not vice versa. Overall, we extend a production function (standard in the literature) by allowing for technology transfers from the parent to its affiliate(s) in the form of intangibles.

In equation (5.6), we come across a 'double identification' challenge: we observe neither the affiliate's nor the parent's TFP. To circumvent this problem we exploit information from the balance sheet of the parent. Estimation of the production function is based on the flexible parametric estimator proposed by Gandhi, Navarro, and Rivers (2016) (herein GNR). In addition to the transmission bias, i.e. firms observing their TFP when choosing their inputs, this estimator controls for the value-added bias that arises from estimating a value-added rather than a gross-output production function. A detailed description of the assumptions, steps followed, and dominance over competing estimators can be found in GNR.[5]

This case considers the classic environment of perfect competition in both the input and output market. Conditional on the state variables and other firm characteristics, the static profit maximisation problem yields the first order condition with respect to the flexible input for the parent:

$$P_t^M = P_t \frac{\partial}{\partial M_t} H(K_{i0t}, L_{i0t}, M_{i0t}) \mathrm{e}^{\omega_{i0t}} \mathcal{E}_p \tag{5.7}$$

and the affiliate:

$$P_t^M = P_t \frac{\partial}{\partial M_t} F(K_{ijt}, L_{ijt}, M_{ijt}) (\Omega_{i0t})^{\beta} \mathrm{e}^{\omega_{ijt}} \mathcal{E}_a \tag{5.8}$$

where P_t^M and P_t are the price of material and output, respectively. Under perfect competition in input and output markets, they are constant across parent and affiliates within the same country and industry, but can vary across time. By the time firms make their annual decisions, ex-post shocks ϵ_{i0t} and ϵ_{ijt} are not in their information sets. Hence, all firms form similar expectations, $\mathcal{E}_p = E(\mathrm{e}^{\epsilon_{i0t}})$ and $\mathcal{E}_a = E(\mathrm{e}^{\epsilon_{ijt}})$.[6] It is important to

[5]See GNR for an exposition of the sizeable effects of value-added bias on TFP heterogeneity. In Chapter 3, my co-author and I show the impact of such a misspecification when estimating learning by doing effects.

[6]We inherently assume that the existence of any measurement error is symmetric across firms and

account and correct for this term since ignoring it, i.e. $\mathcal{E}_p = \mathcal{E}_a = 1$, inherently implies that we move from the mean to the median central tendency of $e^{\epsilon_{ijt}}$ (see Goldberger, 1968).

We retrieve a share for the parent by combining (5.7) with (5.2) and re-arranging terms:

$$s_{i0t} = ln\Big(\tilde{\mathcal{H}}(L_{i0t}, K_{i0t}, M_{i0t})\Big) + ln\mathcal{E}_p - \epsilon_{i0t} \tag{5.9}$$

Similarly, we retrieve a share for the affiliate by combining (5.8) with (5.6):

$$s_{ijt} = ln\Big(\tilde{\mathcal{F}}(L_{ijt}, K_{ijt}, M_{ijt})\Big) + ln\mathcal{E}_a - \epsilon_{ijt} \tag{5.10}$$

In the above, s_{i0t} and s_{ijt} are the log of the nominal share of material, respectively. $\tilde{\mathcal{H}}(K_{i0t}, L_{i0t}, M_{i0t}) = \frac{\partial}{\partial m_{i0t}} h(k_{i0t}, l_{i0t}, m_{i0t})$ and $\tilde{\mathcal{F}}(K_{ijt}, L_{ijt}, M_{ijt}) = \frac{\partial}{\partial m_{ijt}} f(k_{ijt}, l_{ijt}, m_{ijt})$ are the output elasticities of material, i.e. the flexible input. Note that the share equation for the parent is net of the productivity term ω_{i0t}, inducing the transmission bias. The same holds for the affiliate, where, in addition to ω_{ijt}, the 'extra' intangible input $(\Omega_{i0t})^{\beta}$ is also eliminated.

In line with most proxy variable methods, the GNR procedure follows two-steps. In the first step, a Non Linear Least Squares (NLLS) estimation for each of the share equations (5.9) and (5.10) is applied, with:

$$\tilde{\mathcal{H}}(K_{i0t}, L_{i0t}, M_{i0t})\mathcal{E}_p = \sum_{r_k+r_l+r_m \leq r} \gamma'_{r_k,r_l,r_m} k_{i0t}^{r_k} l_{i0t}^{r_l} m_{i0t}^{r_m}, \ with \ \ r_k, r_l, r_m \geq 0 \tag{5.11}$$

and

$$\tilde{\mathcal{F}}(K_{ijt}, L_{ijt}, M_{ijt})\mathcal{E}_a = \sum_{r_k+r_l+r_m \leq r} \delta'_{r_k,r_l,r_m} k_{ijt}^{r_k} l_{ijt}^{r_l} m_{ijt}^{r_m}, \ with \ \ r_k, r_l, r_m \geq 0 \tag{5.12}$$

approximated by a polynomial series estimator of order r. This step identifies ϵ_{i0t} and ϵ_{ijt} (hence $\mathcal{E}_p$ and $\mathcal{E}_a$) and the output elasticity of the flexible input, i.e. material, for both the parent and affiliate.

thus does not affect our results.

By integrating up the output elasticity of the flexible input for the parent:

$$\int \frac{\tilde{\mathcal{H}}(K_{i0t}, L_{i0t}, M_{i0t})}{M_{i0t}} dM_{i0t} = ln\Big(H(K_{i0t}, L_{i0t}, M_{i0t})\Big) + \mathcal{H}(K_{i0t}, L_{i0t}) \tag{5.13}$$

and the affiliate:

$$\int \frac{\tilde{\mathcal{F}}(K_{ijt}, L_{ijt}, M_{ijt})}{M_{ijt}} dM_{ijt} = ln\Big(F(K_{ijt}, L_{ijt}, M_{ijt})\Big) + \mathcal{F}(K_{ijt}, L_{ijt}) \tag{5.14}$$

we identify the production function of the parent and the affiliate up to an unknown constant of integration $\mathcal{H}(k_{i0t}, l_{i0t})$ and $\mathcal{F}(k_{ijt}, l_{ijt})$, respectively. By subtracting the production functions (5.2) and (5.6) from (5.13) and (5.14), respectively, we retrieve the following equations for parent TFP:

$$\omega_{i0t} = \hat{\mathcal{Y}}_{i0t} + \mathcal{H}(k_{i0t}, l_{i0t}) \tag{5.15}$$

and affiliate TFP:

$$\omega_{ijt} = \hat{\mathcal{Y}}_{ijt} + \mathcal{F}(k_{ijt}, l_{ijt}) - \beta\omega_{i0t} \tag{5.16}$$

where $\hat{\mathcal{Y}}_{i0t}$ and $\hat{\mathcal{Y}}_{ijt}$ are the log of the expected output net of the computed integral of the output elasticity of materials for the parent (5.13) and affiliate (5.14), respectively, as estimated from the first stage. $\mathcal{H}(k_{i0t}, l_{i0t})$ and $\mathcal{F}(k_{ijt}, l_{ijt})$ represent the remaining part of the production function to be identified for the parent and affiliate, respectively, and are approximated by a polynomial of degree ν both for the parent:

$$\mathcal{H}(k_{i0t}, l_{i0t}) = \sum_{\nu_k+\nu_l \leq \nu} \pi_{\nu_k,\nu_l} k_{i0t}^{\nu_k} l_{i0t}^{\nu_l}, \ with \ \ \nu_k, \nu_l > 0 \tag{5.17}$$

and the affiliate:

$$\mathcal{F}(k_{ijt}, l_{ijt}) = \sum_{\nu_k+\nu_l \leq \nu} \alpha_{\nu_k,\nu_l} k_{ijt}^{\nu_k} l_{ijt}^{\nu_l}, \ with \ \ \nu_k, \nu_l > 0 \tag{5.18}$$

Combining equations (5.15)-(5.18), we express parent TFP:

$$\omega_{i0t}(\pi_\nu) = \hat{\mathcal{Y}}_{i0t} + \sum_{\nu_k+\nu_l \leq \nu} \pi_{\nu_k,\nu_l} k_{i0t}^{\nu_k} l_{i0t}^{\nu_l} \tag{5.19}$$

and affiliate TFP:

$$\omega_{ijt}(\alpha_\nu, \pi_\nu, \beta) = \hat{\mathcal{Y}}_{ijt} + \sum_{\nu_k+\nu_l \leq \nu} \alpha_{\nu_k,\nu_l} k_{ijt}^{\nu_k} l_{ijt}^{\nu_l} - \beta \left(\hat{\mathcal{Y}}_{i0t} + \sum_{\nu_k+\nu_l \leq \nu} \pi_{\nu_k,\nu_l} k_{i0t}^{\nu_k} l_{i0t}^{\nu_l} \right) \tag{5.20}$$

as functions of variables observed in the data (l and k), variables generated ($\hat{\mathcal{Y}}$), and parameters to be estimated $\alpha_\nu = (\alpha_k, \alpha_l, \ldots, \alpha_{\nu_k,\nu_l})$, $\pi_\nu = (\pi_k, \pi_l, \ldots, \pi_{\nu_k,\nu_l})$ and β.

We proceed in the second step by exploiting the assumption over the law of motion of TFP. We assume that ω_{ijt} evolves over time according to the following stochastic process:

$$\omega_{ijt} = E[\omega_{ijt}|\mathcal{I}_{t-1}] + \xi_{ijt} \tag{5.21}$$

where ξ_{ijt} captures, unanticipated at $t-1$, exogenous shocks that affect affiliate's TFP in t, i.e. $E[\xi_{ijt}|\mathcal{I}_{t-1}] = 0$. Similar to the seminal work of Olley and Pakes (1996), an 'exogenous' first order Markov process can be assumed, i.e. $\omega_{ijt} = E[\omega_{ijt}|\omega_{ijt-1}] + \xi_{ijt}$. However, exogeneity should be relaxed in order to accommodate the fact that TFP evolves endogenously in response to the affiliate's actions. This has been shown for the case of R&D by Aw et al. (2008) and Doraszelski and Jaumandreu (2013); the case of importing by Kasahara and Rodrigue (2008); the case of exporting by De Loecker (2013); and the case of changes in firms' operating environment, i.e. removing trade barriers, by De Loecker (2011). Taking this into account, we use the controlled Markov process in (5.21) to explicitly allow for certain elements of $\mathcal{I}_{t-1}$ to affect TFP. For the baseline specification of our application, the expectation of affiliate TFP conditional on the information at $t-1$ is:

$$\omega_{ijt} = \rho_a \omega_{ijt-1} + \rho_p \omega_{i0t-1} + \phi_t + \phi_{sa} + \phi_{sp} + \phi_{ca} + \phi_{cp} + \xi_{ijt} \tag{5.22}$$

where, in addition to lagged affiliate TFP, lagged parent TFP is allowed to affect current affiliate TFP (in expectation).[7] Also, ϕ_t, ϕ_{sa}, ϕ_{sp}, ϕ_{ca} and ϕ_{cp} are unobserved terms reflecting shocks/characteristics that vary over time (t), across industries of the affiliate (sa), industries of the parent (sp), country of the affiliate (ca) and country of the parent (cp), respectively.[8]

[7]With lagged values, we inherently assume that it takes one period for actions to affect TFP. Such an assumption can be relaxed and tested for robustness against alternative specifications with deeper lags.

[8]One can consider a more general functional form for equation (5.22) by introducting a sieve of the relevant controls. However, this case should be considered with caution since non-linearities in the

We can now express the 'innovation' of affiliate TFP (ξ_{ijt}) as a function of the parameters of the production function to be estimated $(\alpha_\nu, \pi_\nu, \beta)$ by regressing ω_{ijt} on ω_{jit-1}, ω_{i0t-1} and a battery of fixed effects controlling for the unobserved terms in equation (5.22). Note that, as in the case of current $\omega_{ijt}(\alpha_\nu, \pi_\nu, \beta)$ and lagged affiliate TFP $\omega_{ijt-1}(\alpha_\nu, \pi_\nu, \beta)$, our variable of interest, $\omega_{i0t-1}(\pi_\nu)$, is expressed as a function of the unknown parameters of the production function of the parent. Therefore, their effect on future TFP is directly estimated within the second step (described below).

The second step proceeds with a standard iterative Generalised Method of Moments (GMM). To estimate the parameters of interest, $(\alpha_\nu, \pi_\nu, \beta)$, we form a GMM criterion function that is based on the following moment conditions:

$$E\left[\xi_{ijt}(\alpha_\nu, \pi_\nu, \beta) \otimes \mathcal{Z}'_\nu\right] = 0 \tag{5.23}$$

where $\mathcal{Z}_\nu = \left(k_{ijt}, l_{ijt}, \ldots, k_{ijt}^{\nu_k} l_{ijt}^{\nu_l}, k_{i0t}, l_{i0t}, \ldots, k_{i0t}^{\nu_k} l_{i0t}^{\nu_l}, \hat{\mathcal{Y}}_{i0t-1}\right)$ is the 'instrument matrix' with its column space dimension depending on the degree ν of the polynomials used to approximate the constants of integration in (5.17) and (5.18). The orthogonality conditions directly depend on the timing assumptions of the inputs. Capital and labour, for both the parent and the affiliate, are predetermined and thus orthogonal to the innovation to productivity.[9] These instruments are typical in the literature and allow us to identify α_ν and π_ν. However, in order to identify β we use lagged values of $\hat{\mathcal{Y}}_{i0t-1}$ (generated from the first stage), which are uncorrelated with the unanticipated innovation to productivity at time $t-1$.

By minimising the sample analogue of (5.23), we retrieve estimates for parameters of the production technology of the parent (π_ν) and the production technology of the affiliate (α_ν, β).[10] We also retrieve estimates for the persistence of affiliate TFP (ρ_a), the learning by the parent's TFP (ρ_p) and all of the fixed-effects in equation (5.22).

As such, for a polynomial of degree two for both the elasticities of material, $r = 2$, and the constants of integration, $\nu = 2$, the estimated flexible parametric gross-output

fixed-effects would saturate the model, resulting in the incidental parameters problem.

[9]However, if labour is assumed to be a dynamic input then current labour and productivity are correlated and thus the instruments should contain lagged values of labour.

[10]For the baseline specification we use a polynomial of degree two, i.e. $\nu = 2$. This means that the parameters to be estimated are: $\alpha_2 = (\alpha_k, \alpha_l, \alpha_{kk}, \alpha_{ll}, \alpha_{kl})$, $\pi_2 = (\pi_k, \pi_l, \pi_{kk}, \pi_{ll}, \pi_{kl})$ and β, and the instruments used are: $\mathcal{Z}_2 = (k_{ijt}, l_{ijt}, k_{ijt}^2, l_{ijt}^2, k_{ijt}l_{ijt}, k_{i0t}, l_{i0t}, k_{i0t}^2, l_{i0t}^2, k_{i0t}l_{i0t}, \hat{\mathcal{Y}}_{i0t-1})$.

production function for the parent is:

$$
\begin{aligned}
y_{i0t} = \big(&\gamma_0 + \gamma_k k_{i0t} + \gamma_l l_{i0t} + \frac{\gamma_m}{2} m_{i0t} + \gamma_{kk} k_{i0t}^2 + \gamma_{ll} l_{i0t}^2 + \frac{\gamma_{mm}}{3} m_{i0t}^2 \\
&+ \gamma_{kl} k_{i0t} l_{i0t} + \frac{\gamma_{km}}{2} k_{i0t} m_{i0t} + \frac{\gamma_{lm}}{2} l_{i0t} m_{i0t} + \frac{\gamma_{klm}}{2} k_{i0t} l_{i0t} m_{i0t}\big)\ m_{i0t} \\
&- \pi_k k_{i0t} - \pi_l l_{i0t} - \pi_{kk} k_{i0t}^2 - \pi_{ll} l_{i0t}^2 - \pi_{kl} k_{i0t} l_{i0t} + \omega_{i0t} + \epsilon_{i0t}
\end{aligned} \tag{5.24}
$$

and for the affiliate is:

$$
\begin{aligned}
y_{ijt} = \big(&\delta_0 + \delta_k k_{ijt} + \delta_l l_{ijt} + \frac{\delta_m}{2} m_{ijt} + \delta_{kk} k_{ijt}^2 + \delta_{ll} l_{ijt}^2 + \frac{\delta_{mm}}{3} m_{ijt}^2 \\
&+ \delta_{kl} k_{ijt} l_{ijt} + \frac{\delta_{km}}{2} k_{ijt} m_{ijt} + \frac{\delta_{lm}}{2} l_{ijt} m_{ijt} + \frac{\delta_{klm}}{2} k_{ijt} l_{ijt} m_{ijt}\big)\ m_{ijt} \\
&- \alpha_k k_{ijt} - \alpha_l l_{ijt} - \alpha_{kk} k_{ijt}^2 - \alpha_{ll} l_{ijt}^2 - \alpha_{kl} k_{ijt} l_{ijt} + \beta \omega_{i0t} + \omega_{ijt} + \epsilon_{ijt}
\end{aligned} \tag{5.25}
$$

Based on estimates of the production function coefficients, we can now compute other relevant variables, i.e. TFP, output elasticities of inputs and returns to scale (RTS), for both the parent and affiliate, using equations (5.19) and (5.20), respectively.

Finally, note that our TFP estimates are revenue based since we do not observe physical output, but only monetary values deflated at the industry level. Results should be interpreted bearing this in mind (Klette and Griliches, 1996).[11]

5.3 Data

We construct a firm-level panel of manufacturing firms from 16 EU countries[12] for the period 2004 to 2013. Data come from the Amadeus database by Bureau van Dijk Electronic Publishing (2011) (BvDEP). BvDEP regularly updates the information set in Amadeus and releases a DVD containing the latest information on ownership on a monthly basis. Firms that exit the market are dropped fairly rapidly. In order to have a complete set of financial and ownership information over time, we use a time series of (annual) DVDs to construct a consistent database. In particular, we build a dataset with nearly full financial and administrative information, i.e. balance sheet, profit and loss

[11] A future extension of the empirical model will control for unobserved variation in firm-specific prices, by introducing more structure and assumptions. This includes an iso-elastic demand system coupled with monopolistic competition, similar to Klette and Griliches (1996) and De Loecker (2011).

[12] These include Austria, Belgium, Bulgaria, Czech Republic, Germany, Spain, Finland, France, Croatia, Italy, Latvia, Netherlands, Norway, Poland, Sweden and Slovakia.

account activities, location, ownership, exit and entry. Merlevede et al. (2015) describe the construction and representativeness of the data at length.

We focus on the sample of affiliate firms. Of these firms, more than 50% of their shares are owned by a domestic or foreign parent firm. Each affiliate can have only one majority controlling parent, while parent firms can control multiple affiliates. We keep the active manufacturing[13] firms that file unconsolidated accounts.[14] We retain firms which report operating revenue turnover, tangible fixed assets, number of employees, material costs, NACE Rev.2 2-digit industry classification and ownership information. Firms with less than two years of data are removed from the sample. We also remove outliers using the BACON method proposed by Billor et al. (2000).[15] This results in an unbalanced European panel of 4987 parent and 6311 affiliate firms with full balance sheet information on both sides for the period 2004-2013 (see Table 5.1).

Table 5.1: Summary Statistics

Affiliates' ...	Obs.	Mean	St.Dev.	p25	p50	p75
$Output^{\dagger}$	28469	47	228	2.1	6.8	25
$Capital^{\dagger}$	28469	12	60	.18	1	4.7
$Material^{\dagger}$	28469	30	164	.85	3.3	13
$Labour$	28469	94	250	12	31	87
$Wages$	28409	61637	90875	31633	39962	51392
Parents' ...						
$Output^{\dagger}$	22958	143	534	8.9	24	83
$Capital^{\dagger}$	22958	30	125	1.1	3.9	14
$Material^{\dagger}$	22958	84	357	3.9	12	44
$Labour$	22958	325	1058	38	91	259
$Wages$	22913	62190	83260	35467	43663	55058
$Affiliates$	22958	1.2	.72	1	1	1

Notes: † monetary variables in million Euro. BvDEP database for manufacturing firms in 16 EU countries for the period 2004 to 2013.

All monetary variables are deflated using the appropriate country-NACE Rev.2 2-digit output deflator from the EU KLEMS database. (Real) *Output* (Y) is operating

[13] Table 5.A.1 in Appendix 5.A provides an overview of the NACE Rev.2 2-digit industries included and their correspondence to the more aggregate A*38 code that represents intermediate SNA/ISIC aggregation.

[14] This refers to accounts not integrating the statements of possible controlled subsidiaries or branches of the concerned company.

[15] BACON stands for Block Adaptive Computationally efficient Outlier Nominators. It is a multiple outlier detection method. The variables considered in the method are log of output, labour, capital and material.

revenue turnover deflated with producer price indices. *Capital* (K) is tangible fixed assets deflated by the average of the deflators of various NACE Rev.2 2-digit industries (Javorcik, 2004b).[16] (Real) *Material* (M) is material inputs deflated by an intermediate input deflator constructed as a weighted average of output deflators, where country-time-industry specific weights are based on intermediate input uses retrieved from input-output tables. *Labour* (L) is the number of employees. *Wages* is the cost of employees divided by the number of employees and *Affiliates* refers to the number of majority controlled affiliates from each parent.

5.4 Results

In this section we first assess the extent to which parent TFP contributes to the final output of the affiliate. We measure this as the affiliate's output elasticity of parent TFP – similar to other tangible inputs, i.e. labour, capital and material. We then analyse in detail whether such transfers of intangible technology constitute potential determinants of the affiliate's TFP evolution via learning mechanisms. Finally we discus the importance of intellectual property/patent rights as a potential barrier to the flow of intangible inputs within the boundaries of the firm and provide a pseudo-placebo test to support the validity of our methodological approach.

5.4.1 Intangible Technology Transfers

In Table 5.2 we report estimates for the production function of the affiliate. In column 1, we consider the sample of affiliates from any type of ownership structure. Capital, labour and material contribute significantly to the production technology of the affiliate, as shown from their respective output elasticities in the first three rows of column 1. The relative importance of each factor is in line with the extensively reported estimates of output elasticities in the production function literature.

The estimates of β show that parent TFP is a significant input in the affiliate's production technology. In column 1, a one percentage point increase in the TFP of the parent leads to a 0.06% increase in the affiliate's output. The extent to which parent TFP

[16] Electrical equipment (27); machinery and equipment n.e.c. (28); motor vehicles, trailers and semi-trailers (29); and other transport equipment (30).

contributes to the affiliate's final output is roughly more than half of the contribution from the affiliate's physical capital (0.11%). If we were to ignore such transfers, our results imply that the term $\beta\omega_{i0t}$ from equation (5.6) would be falsely subsumed in the affiliate TFP. In turn, this coefficient would be overestimated by roughly 12%. This underscores the fact that parent TFP is an important transfer of intangible technology to the affiliate that should be modelled accordingly.

Table 5.2: Affiliate's Production Function Estimates

	(1) *All*	(2) *Domestic*	(3) *Foreign*
$\bar{\hat{\theta}}^k_{ijt}$	0.112***	0.099***	0.144***
	(0.007)	(0.007)	(0.017)
$\bar{\hat{\theta}}^l_{ijt}$	0.347***	0.377***	0.195***
	(0.013)	(0.014)	(0.021)
$\bar{\hat{\theta}}^m_{ijt}$	0.461***	0.446***	0.553***
	(0.004)	(0.004)	(0.006)
β	0.063***	0.063***	0.044***
	(0.006)	(0.006)	(0.013)
$\bar{\hat{RTS}}_{ijt}$	0.982***	0.986***	0.937***
	(0.010)	(0.011)	(0.019)
$\bar{\hat{RTS}}_{ijt} - 1$	-0.018*	-0.014	-0.063***
	(0.010)	(0.011)	(0.019)
Observations	20009	17145	3029

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all manufacturing firms. $\bar{\hat{\theta}}^k_{ijt}$, $\bar{\hat{\theta}}^l_{ijt}$ and $\bar{\hat{\theta}}^m_{ijt}$ are averages of estimated output elasticities of capital, labour and material, respectively. $\bar{\hat{RTS}}_{ijt}$ is the average of the estimated RTS. All estimates include additive year, industry-affiliate, industry-parent, country-affiliate and country-parent fixed effects, if applicable. Standard errors are block-bootstrapped with 500 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

By adding up all output elasticities we retrieve the RTS for the production function of the affiliate. With weak significance, we reject constant RTS in the last row. However, this is expected to be a direct outcome of the fact that we estimate revenue production functions and, as such, the coefficients of the production function would be downward biased in the presence of output-price differences across firms (Klette and Griliches, 1996;

De Loecker, 2011).[17]

In columns 2 and 3, we split the sample into domestic and foreign affiliates, respectively. We find that domestic affiliates have output elasticities that are on average larger for labour, and lower for capital and material relative to foreign affiliates. Moreover, we find a smaller estimated affiliate output elasticity of parent TFP for foreign affiliates. This confirms suggestive evidence that transfers of knowledge, know-how and technology from parent to foreign affiliates are less likely in distorted institutional environments (Moran, 2007), e.g. less intellectual property rights (Branstetter et al., 2006). Based on a theoretical model of optimal knowledge, Gumpert (2015) shows that the presence of cross-border communication costs would decrease the frequency with which foreign affiliates and their parents actively exchange, and force the foreign affiliate to depend more on learning practices.[18] Our results confirm the former part of the argument, and test the latter in the following subsection.

Overall, we see that parent TFP, used as a measure of intangible input accessed by the affiliate within firm boundaries, is a significant determinant of the affiliate's production technology.

5.4.2 Learning

In Table 5.3, we report estimates for the affiliate's markov process proposed in equation (5.22). As before, the table consists of three columns where results cover all, domestic and foreign affiliates, respectively. Fixed effects used in the estimations are not reported in the tables due to space considerations and their non-relevant economic interpretation in this context.

In the bottom row of column 1, we see that parent TFP is a significant determinant of future affiliate TFP. The coefficient estimates suggest that a one standard deviation increase in lagged parent TFP increases current affiliate TFP by 0.15%. Due to the

[17] In this case, we also expect the parameters estimated for both the intangible technology transfers, i.e. β, and the parent's production function to be 'under-under-estimated.' This is because the estimated productivity of the parent would already be downward biased from any price differences in the output market of the parent. If foreign parents charge on average higher (lower) prices than domestic parents, this will result in a larger (smaller) downward bias for the affiliates with foreign parents.

[18] The parent avoids such communication costs by assigning more knowledge to their foreign affiliates. This helps to explain why foreign affiliates have higher wages and sales relative to domestic affiliates. We confirm that such differences are prevalent in our data and also exist across other dimensions of the firm, i.e. labour, capital and materials, when comparing Tables 5.A.2 and 5.A.3 in Appendix 5.A.

assumed Hicks-neutrality in TFP, this effect is also interpreted as an equivalent increase in affiliate output. In the short-run, this is a directly comparable effect and is roughly one third of the importance of intangible technology transfers from the parent (estimated in the previous section). However, in the long-run, this effect dominates and allows affiliates to experience TFP increases that amount to an average 23% of any increase in parent TFP. In other words, the affiliate's learning capacity is on average one forth of parent TFP growth.[19]

Table 5.3: Affiliates's Markov Process Estimates

	(1) *All*	(2) *Domestic*	(3) *Foreign*
ρ_a	0.915***	0.911***	0.923***
	(0.011)	(0.009)	(0.020)
ρ_p	0.023***	0.022**	0.030**
	(0.008)	(0.009)	(0.014)
Observations	20009	17145	3029

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all manufacturing firms. All estimates include additive year, industry-affiliate, industry-parent, country-affiliate and country-parent fixed effects, if applicable. Standard errors are block-bootstrapped with 500 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

In columns 2 and 3 we find that this learning effect is larger for foreign versus domestic affiliates. In the long-run, foreign affiliates appear to learn/absorb 8% more from the technology transferred from the parent than domestic affiliates. This result supports the theoretical view that foreign affiliates master from a higher share of the production process by themselves, due to the presence of high cross-border communication costs (Gumpert, 2015).

5.4.3 Intellectual Property Rights

Communication barriers can be expressed in various forms; ranging from physical distance to institutional differences. In this subsection we explore the relevance of

[19]A one standard deviation increase in parent TFP leads to a 1.75% increase in affiliate TFP in the long-run.

intellectual property rights (IPR) as a potential source of communication costs within the boundaries of the firm. Specifically, we examine the extent to which differences in IPR influence technology transfers within ownership structures.[20]

To proceed, we construct a measure of IPR 'distance' (IPR) as the difference in the level of protection on patent rights between the country of the parent and that of its affiliate. For empirical robustness, we compute this measure using two different indices on the protection of property rights.

First, we use the quinquennial country-specific index of patent rights protection developed by Ginarte and Park (1997) and updated by Park (2008). The index is constructed as the unweighted sum of five sub-indices ranging between zero and one and covering the following categories: duration of protection; enforcement; coverage; provisions for loss of protection; and membership in international patent treaties. As such, the index ranges between zero and five, with higher values indicating stronger levels of patent rights protection.[21]

Second, we use a new country-year specific index on the protection of property rights proposed by Ouattara and Standaert (2017). Based on a sate-space model, they combine all publicly available information on property rights into an index where higher values indicate stronger levels of property rights protection.

In both cases, we interpret IPR as a form of 'institutional distance,' where higher values indicate a decline in the affiliate's IPR institutional environment relative to that of its parent. Note that the indices used to compute IPR are both at the country level and thus IPR is by construction zero for all domestically owned affiliates.

We now extend our empirical model to allow for IPR to explain potential heterogeneity in intra-firm transfers of intangible technology and, in turn, heterogeneity in productivity effects via learning mechanisms. Below we describe the main differences from the methodology used previously. The production function of the affiliate (5.6) becomes:

$$y_{ijt} = f(k_{ijt}, l_{ijt}, m_{ijt}) + \beta_p \; \omega_{i0t} + \beta_{IPR} \; IPR_{ct} + \beta_{pIPR} \; \omega_{i0t} \; IPR_{ct} + \omega_{ijt} + \epsilon_{ijt} \quad (5.26)$$

[20]For studies on the relationship between IPR and international technology transfers see Javorcik (2004a), Park and Lippoldt (2005) and Branstetter et al. (2006).

[21]Given that the index is only available quinquennially between 1960 and 2010, we carry forward the values from the years 2000, 2005 and 2010 in order to retrieve annual series for the period considered in our firm-level sample, i.e. 2004-2013.

where now we also include the IPR measure and its interaction with parent TFP. Similarly, the controlled Markov process (5.22) becomes:

$$\begin{aligned}\omega_{ijt} = &\rho_a \omega_{ijt-1} + \rho_p \ \omega_{i0t-1} + \rho_{IPR} \ IPR_{ct-1} + \rho_{pIPR} \ \omega_{i0t-1} \ IPR_{ct-1} + \\ &\phi_t + \phi_{sa} + \phi_{sp} + \phi_{ca} + \phi_{cp} + \xi_{ijt}\end{aligned} \tag{5.27}$$

where, on top of the previous determinants, we also allow for lagged IPR and its interaction with lagged parent TFP to affect current affiliate TFP (in expectation).

The parameter space to be estimated has increased since β and ρ are not single parameters anymore, but instead are vectors of parameters, i.e. $(\beta_p, \beta_{IPR}, \beta_{pIPR})$ and $(\rho_p, \rho_{IPR}, \rho_{pIPR})$, respectively. This implies that we need to find new instruments for the identification of the additional parameters considered. The new 'instrument matrix' is $\tilde{\mathcal{Z}}_\nu = \left(k_{ijt}, l_{ijt}, \ldots, k_{ijt}^{\nu_k} l_{ijt}^{\nu_l}, k_{i0t}, l_{i0t}, \ldots, k_{i0t}^{\nu_k} l_{i0t}^{\nu_l}, \hat{\mathcal{Y}}_{i0t-1}, IPR_{ct-1}, \hat{\mathcal{Y}}_{i0t-1} IPR_{ct-1}\right)$, where lag values of IPR and their interaction with lagged values of $\hat{\mathcal{Y}}_{i0t-1}$ are expected to be orthogonal to the unanticipated innovation to productivity at time $t-1$.

Following the same steps and estimation strategy from Section 5.2, we retrieve the parameters of interest. However, since the IPR measure is by construction zero for all domestically owned affiliates, we only consider the sample of foreign owned affiliates. Otherwise, the variation in the IPR measure is either limited for the full sample or nonexistent for the sample of domestically owned affiliates. In each of the tables presented below, we report two columns, *G&P* (2008) and *O&S* (2017), respectively. The first column refers to the case where IPR is computed using data from Ginarte and Park (1997) and Park (2008) while the second column uses data from Ouattara and Standaert (2017).

In Table 5.4 we report estimates for the production function of the affiliate (5.26).[22] On the one hand, the estimates of β_p confirm our previous findings that parent TFP, as a measure of an intangible input accessed by the affiliate, is a significant intangible input in the affiliate's production technology. On the other hand, estimates for β_{IPR} and β_{pIPR} suggest that IPR is insignificant in explaining both differences in the affiliate's production technology as well as any differential effects of intangible technology transfers from the parent, respectively.

[22]Note that the output elasticities for capital, labour and material are similar to those in Table 5.2 and are thus not reported for space considerations.

Table 5.4: Affiliate's Production Function Estimates with IPR

	(1) *G&P* (2008)	(2) *O&S* (2017)
β_p	0.050***	0.044***
	(0.015)	(0.016)
β_{IPR}	-0.739	-0.087
	(2.057)	(0.103)
β_{pIPR}	0.025	0.001
	(0.043)	(0.002)
Observations	2935	3029

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all manufacturing firms. All estimates include additive year, industry-affiliate, industry-parent, country-affiliate and country-parent fixed effects, if applicable. Standard errors are block-bootstrapped with 500 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

Table 5.5: Affiliates's Markov Process Estimates with IPR

	(1) *G&P* (2008)	(2) *O&S* (2017)
ρ_a	0.925***	0.921***
	(0.016)	(0.018)
ρ_p	0.027***	0.032***
	(0.009)	(0.011)
ρ_{IPR}	1.541	0.063
	(1.273)	(0.055)
ρ_{pIPR}	-0.028	-0.001
	(0.026)	(0.001)
Observations	2935	3029

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all manufacturing firms. All estimates include additive year, industry-affiliate, industry-parent, country-affiliate and country-parent fixed effects, if applicable. Standard errors are block-bootstrapped with 500 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

In Table 5.5, we report estimates for the affiliate's markov (5.27). As before, parent TFP is a significant determinant of future affiliate TFP. However, estimates for ρ_{IPR} and ρ_{pIPR} indicate no significant learning from changes in the IPR 'distance' as well as no differential learning effects from transfers of intangible technology due to changes in IPR.

Overall, we find that differences in the IPR levels of foreign owned affiliates do not qualify as a potential source of communication costs within the boundaries of the firm. This implies that such differences are unlikely to mitigate the transfer of intangible technology from the parent or, in turn, increase the affiliate's future productivity through learning mechanisms. Note that we should interpret these findings with a grain of salt since results could be driven by the limited variation in the IPR measure. If anything, further robustness checks are needed to explore other relevant sources of variation that could support the presence of communication barriers and thus explain potential heterogeneity in the estimated results.

5.4.4 Pseudo-Placebo Test

In this subsection we validate our results by performing a set of pseudo-placebo tests. Specifically, we match parent and/or affiliate firms with domestic firms which do not have ownership links. We perform Mahanalobis' distance matching based on characteristics (i.e. output, capital, labour and materials) observed in the first year that the firm appears in the treated sample. An additional restriction is that the matched firm should provide information for at least the same number of years that the original firm exists in our sample. Subsequently, we re-run the same estimation procedure described above and compare estimated outcomes. In each of the Tables 5.6 and 5.7 presented below, column (1) refers to the the original non-matched sample and columns (2)-(4) refer to the controlled samples where the match is conducted for the affiliate, the parent, and both the affiliate and the parent, respectively.

Results indicate that the effects stemming from both transfers of intangibles between the parent and its affiliate(s), and effects on the future productivity of affiliates, respectively, are smaller in magnitude than found previously. Although any significant result may seem counter-intuitive at first, a statistically significant effect can be explained by spillovers

Table 5.6: Affiliate's Production Function Estimates with Matched Samples

	Original	Matched wrt.		
	Sample	af	pa	af & pa
$\bar{\hat{\theta}}^{k}_{ijt}$	0.123***	0.174***	0.128***	0.172***
	(0.009)	(0.015)	(0.010)	(0.014)
$\bar{\hat{\theta}}^{l}_{ijt}$	0.334***	0.308***	0.337***	0.310***
	(0.016)	(0.025)	(0.016)	(0.024)
$\bar{\hat{\theta}}^{m}_{ijt}$	0.459***	0.450***	0.459***	0.450***
	(0.005)	(0.005)	(0.005)	(0.005)
β	0.077***	0.037***	0.049***	0.038***
	(0.008)	(0.007)	(0.007)	(0.007)
$R\bar{\hat{T}}S_{ijt}$	0.992***	0.969***	0.972***	0.969***
	(0.013)	(0.017)	(0.013)	(0.016)
$R\bar{\hat{T}}S_{ijt} - 1$	-0.008	-0.031*	-0.028**	-0.031*
	(0.013)	(0.017)	(0.013)	(0.016)
Observations	10122	10122	10122	10122

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all manufacturing firms. All estimates include additive year, industry-affiliate, industry-parent, country-affiliate and country-parent fixed effects, if applicable. Standard errors are block-bootstrapped with 500 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

Table 5.7: Affiliates's Markov Process Estimates with Matched Samples

	Original	Matched wrt.		
	Sample	af	pa	af & pa
ρ_α	0.917***	0.933***	0.920***	0.933***
	(0.011)	(0.017)	(0.014)	(0.017)
ρ_p	0.030**	0.013*	0.020**	0.016**
	(0.012)	(0.007)	(0.010)	(0.007)
Observations	10122	10122	10122	10122

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all manufacturing firms. All estimates include additive year, industry-affiliate, industry-parent, country-affiliate and country-parent fixed effects, if applicable. Standard errors are block-bootstrapped with 500 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

and/or indirect effects, as well-established in the literature.[23] As such, the presence of smaller effects found when completing the pseudo-placebo tests lends support to the main findings in this chapter. Moreover, these findings open the door for further research on the relative importance of technology transfers outside the boundaries of the firm.

5.5 Conclusion

A large literature has tried to understand the role of firm boundaries. Suggestive empirical evidence points to the theoretically based argument that firm boundaries exist to facilitate the transfer of intangible inputs. In this paper we identify and quantify transfers of intangible inputs, and how they determine both the production technology and productivity evolution of the firm.

We use a carefully constructed European panel of majority owned parent-affiliate groups with full balance sheet information on both sides for the period 2004-2013 and extend a typical production function estimation procedure. Due to the data restrictions on intangible inputs, we devise an empirical method that allows us to characterise the full set of intangibles transferred between parent and affiliates.

We identify, at the firm level, the importance of productivity transfers from various types of ownership structures and confirm the theoretically based argument that firm boundaries exist to facilitate the transfer of intangibles. In addition, we identify a new dimension where transfers of intangible technology are significant determinants of the evolution of the affiliate's productivity. Exploiting the richness of the data, we find that domestically-owned affiliates experience larger technology transfers from their parents, while foreign-owned affiliates benefit more from productivity increases induced by learning mechanisms.

The results presented in this paper are particularly poignant due to inherent difficulties in measuring intangible assets. Therefore, they are highly relevant to both policymakers and institutions insofar as they can provide a strong reference point for shaping future policies on intangible assets.

[23] See Javorcik (2010) for a literature review on technology/knowledge spillovers to domestic firms from foreign direct investment, i.e. foreign affiliates of multinational companies.

Appendix 5.A Additional Figures and Tables

Table 5.A.1: List of NACE Rev.2 2-digit industries in the manufacturing sector.

A*38	Division	Description
CA	10	Manufacture of food products
CA	11	Manufacture of beverages
CA	12	Manufacture of tobacco products
CB	13	Manufacture of textiles
CB	14	Manufacture of wearing apparel
CB	15	Manufacture of leather and related products
CC	16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
CC	17	Manufacture of paper and paper products
CC	18	Printing and reproduction of recorded media
CE	20	Manufacture of chemicals and chemical products
CF	21	Manufacture of basic pharmaceutical products and preparations
CG	22	Manufacture of rubber and plastic products
CG	23	Manufacture of other non-metallic mineral products
CH	24	Manufacture of basic metals
CH	25	Manufacture of fabricated metal products, except machinery & equip.
CI	26	Manufacture of computer, electronic and optical products
CJ	27	Manufacture of electrical equipment
CK	28	Manufacture of machinery and equipment n.e.c.
CL	29	Manufacture of motor vehicles, trailers and semi-trailers
CL	30	Manufacture of other transport equipment
CM	31	Manufacture of furniture
CM	32	Other manufacturing
CM	33	Repair and installation of machinery and equipment

Note: A*38 code refers to the intermediate SNA/ISIC aggregation.

Table 5.A.2: Sumary Statistics for Domestic Ownership

Affiliates' ...	Obs.	Mean	St.Dev.	p25	p50	p75
Output†	24339	28	101	1.8	5.2	17
Capital†	24339	6.8	33	.15	.79	3.5
Material†	24339	17	73	.68	2.5	9.2
Labour	24339	76	203	11	26	71
Wages	24283	54539	75047	31064	38807	49077
Parents' ...						
Output†	20127	124	421	7.7	20	68
Capital†	20127	28	119	.95	3.4	12
Material†	20127	73	275	3.3	10	37
Labour	20127	281	920	34	77	221
Wages	20102	60940	81574	34608	42689	53909
Affiliates	20127	1.2	.68	1	1	1

Notes: † monetary variables in million Euro. BvDEP database for manufacturing firms in 16 EU countries for the period 2004 to 2013.

Table 5.A.3: Sumary Statistics for Foreign Ownership

Affiliates' ...	Obs.	Mean	St.Dev.	p25	p50	p75
Output†	4346	231	908	10	29	101
Capital†	4346	72	507	.73	4.3	20
Material†	4346	150	597	5.4	16	61
Labour	4346	180	358	34	81	188
Wages	4341	148572	427373	37294	49297	72651
Parents' ...						
Output†	3647	276	818	33	82	226
Capital†	3647	46	159	3.3	9.4	28
Material†	3647	160	511	16	39	115
Labour	3647	645	1435	118	254	640
Wages	3620	69211	91029	41750	50015	61600
Affiliates	3647	1.2	.55	1	1	1

Notes: † monetary variables in million Euro. BvDEP database for manufacturing firms in 16 EU countries for the period 2004 to 2013.

Table 5.A.4: Parent's Production Function Estimates

	(1) *All*	(2) *Domestic*	(3) *Foreign*
$\bar{\hat{\theta}}^k_{i0t}$	0.062***	0.059***	0.085**
	(0.006)	(0.009)	(0.039)
$\bar{\hat{\theta}}^l_{i0t}$	0.346***	0.350***	0.310***
	(0.009)	(0.011)	(0.024)
$\bar{\hat{\theta}}^m_{i0t}$	0.474***	0.471***	0.499***
	(0.001)	(0.002)	(0.004)
$R\bar{\hat{T}}S_{i0t}$	0.882***	0.879***	0.893***
	(0.009)	(0.011)	(0.049)
$R\bar{\hat{T}}S_{i0t} - 1$	-0.118***	-0.121***	-0.107**
	(0.009)	(0.011)	(0.049)
Observations	20009	17145	3029

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all manufacturing firms. $\bar{\hat{\theta}}^k_{i0t}$, $\bar{\hat{\theta}}^l_{i0t}$ and $\bar{\hat{\theta}}^m_{i0t}$ are averages of estimated output elasticities of capital, labour and material respectively. $R\bar{\hat{T}}S_{i0t}$ is the average of the estimated RTS. All estimates include additive year, industry-affiliate, industry-parent, country-affiliate and country-parent fixed effects, if applicable. Standard errors are block-bootstrapped with 500 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

References

Abel, A. B. and J. C. Eberly (1994). A unified model of investment under uncertainty. *The American Economic Review 84*(5), 1369–1384.

Abel, A. B. and J. C. Eberly (1998). The mix and scale of factors with irreversibility and fixed costs of investment. In *Carnegie-Rochester Conference Series on Public Policy*, Volume 48, pp. 101–135. Elsevier.

Abowd, J. M. and F. Kramarz (2003). The costs of hiring and separations. *Labour Economics 10*(5), 499 – 530.

Abramovitz, M. (1956). Resource and output trends in the united states since 1870. In *Resource and output trends in the United States since 1870*, pp. 1–23. NBER.

Acemoglu, D., P. Aghion, C. Lelarge, J. Van Reenen, and F. Zilibotti (2007). Technology, information, and the decentralization of the firm. *The Quarterly Journal of Economics 122*(4), 1759–1799.

Acemoglu, D., R. Griffith, P. Aghion, and F. Zilibotti (2010). Vertical integration and technology: Theory and evidence. *Journal of the European Economic Association 8*(5), 989–1033.

Ackerberg, D., C. L. Benkard, S. Berry, and A. Pakes (2007). Econometric tools for analyzing market outcomes. *Handbook of econometrics 6*, 4171–4276.

Ackerberg, D., K. Caves, and G. Frazer (2006). Structural estimation of production functions. *manuscript. Department of Economics, UCLA.*

Ackerberg, D. A., K. Caves, and G. Frazer (2016). Identification properties of recent production function estimators. *Econometrica 83*(6), 2411–2451.

Adda, J. and R. W. Cooper (2003). *Dynamic economics: quantitative methods and applications*. MIT press.

Aguirregabiria, V. and C. Alonso-Borrego (2014). Labor contracts and flexibility: Evidence from a labor market reform in spain. *Economic Inquiry 52*(2), 930–957.

Alvarez, F. and M. Veracierto (2001). Severance payments in an economy with frictions. *Journal of Monetary Economics 47*(3), 477 – 498.

Amiti, M. and J. Konings (2007). Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia. *The American Economic Review 97*(5), 1611–1638.

Amiti, M. and S.-J. Wei (2005). Fear of service outsourcing: is it justified? *Economic Policy 20*(42), 308–347.

Antràs, P., D. Chor, T. Fally, and R. Hillberry (2012). Measuring the upstreamness of production and trade flows. *The American Economic Review 102*(3), pp. 412–416.

Antràs, P., T. C. Fort, and F. Tintelnot (2014). The margins of global sourcing: theory and evidence from us firms.

Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The Review of Economic Studies 58*(2), 277–297.

Argyris, C. (2001). 15 empowerment: The emperor's new clothes. *Creative Management*, 195.

Arnold, J. M. and B. S. Javorcik (2009). Gifted kids or pushy parents? foreign direct investment and plant productivity in indonesia. *Journal of International Economics 79*(1), 42 – 53.

Arrow, K. J. (1962). The economic implications of learning by doing. *The Review of Economic Studies 29*(3), 155–173.

Arrow, K. J. (1968). Optimal capital policy with irreversible investment. *Value, Capital and Growth*, 1–20.

Arrow, K. J. (1975). Vertical integration and communication. *The Bell Journal of Economics 6*(1), 173–183.

Asphjell, M. K., W. Letterie, Ø. A. Nilsen, and G. A. Pfann (2014). Sequentiality versus simultaneity: Interrelated factor demand. *Review of Economics and Statistics 96*(5), 986–998.

Atalay, E. (2014). Materials prices and productivity. *Journal of the European Economic Association 12*(3), 575–611.

Atalay, E., A. Hortaçsu, and C. Syverson (2014, April). Vertical integration and input flows. *American Economic Review 104*(4), 1120–48.

Autor, D. H., W. R. Kerr, and A. D. Kugler (2007). Does employment protection reduce productivity? evidence from us states. *The Economic Journal 117*(521), F189–F217.

Aw, B. Y., X. Chen, and M. J. Roberts (2001). Firm-level evidence on productivity differentials and turnover in taiwanese manufacturing. *Journal of Development Economics 66*(1), 51 – 86.

Aw, B. Y., M. J. Roberts, and D. Y. Xu (2008). R&d investments, exporting, and the evolution of firm productivity. *American Economic Review 98*(2), 451–56.

Aw, B. Y., M. J. Roberts, and D. Y. Xu (2011, June). R&d investment, exporting, and productivity dynamics. *American Economic Review 101*(4), 1312–44.

Baily, M. N., C. Hulten, D. Campbell, T. Bresnahan, and R. E. Caves (1992). Productivity dynamics in manufacturing plants. *Brookings Papers on Economic Activity. Microeconomics 1992*, 187–267.

Balk, B. M. (2016). *The Dynamics of Productivity Change: A Review of the Bottom-Up Approach*, pp. 15–49. Cham: Springer International Publishing.

Bartelsman, E., J. Haltiwanger, and S. Scarpetta (2013, February). Cross-country differences in productivity: The role of allocation and selection. *American Economic Review 103*(1), 305–34.

Bartelsman, E. J. and P. J. Dhrymes (1998). Productivity dynamics: U.s. manufacturing plants, 1972–1986. *Journal of Productivity Analysis 9*(1), 5–34.

Bas, M. and V. Strauss-Kahn (2015). Input-trade liberalization, export prices and quality upgrading. *Journal of International Economics 95*(2), 250 – 262.

Basu, S. and J. G. Fernald (1997). Returns to scale in u.s. production: Estimates and implications. *Journal of Political Economy 105*(2), 249–283.

Böckerman, P. and M. Maliranta (2007). The micro-level dynamics of regional productivity growth: The source of divergence in finland. *Regional Science and Urban Economics 37*(2), 165 – 182.

Benassy, J.-P. (1998). Is there always too little research in endogenous growth with expanding product variety? *European Economic Review 42*(1), 61 – 69.

Bernard, A. B., E. J. Blanchard, I. Van Beveren, and H. Y. Vandenbussche (2012, July). Carry-along trade. Working Paper 18246, National Bureau of Economic Research.

Bernard, A. B. and J. B. Jensen (1999). Exceptional exporter performance: cause, effect, or both? *Journal of International Economics 47*(1), 1 – 25.

Bernard, A. B., I. Van Beveren, and H. Vandenbussche (2014). Multi-product exporters and the margins of trade. *Japanese Economic Review 65*(2), 142–157.

Bertola, G. and R. J. Caballero (1990). Kinked adjustment costs and aggregate dynamics. In *NBER Macroeconomics Annual 1990, Volume 5*, pp. 237–296. MIT Press.

Bertola, G. and R. J. Caballero (1994). Irreversibility and aggregate investment. *The Review of Economic Studies 61*(2), 223–246.

Bilir, L. K. and E. Morales (2016). Innovation in the global firm. Technical report, National Bureau of Economic Research.

Billor, N., A. S. Hadi, and P. F. Velleman (2000). Bacon: blocked adaptive computationally efficient outlier nominators. *Computational Statistics & Data Analysis 34*(3), 279 – 298.

Blalock, G. and P. J. Gertler (2008). Welfare gains from foreign direct investment through technology transfer to local suppliers. *Journal of International Economics 74*(2), 402 – 421.

Blalock, G. and F. M. Veloso (2007). Imports, productivity growth, and supply chain learning. *World Development 35*(7), 1134 – 1151.

Blanas, S. and A. Seric (2017a). Determinants of intra-firm trade. Working Papers 178118175, Lancaster University Management School, Economics Department.

Blanas, S. and A. Seric (2017b). Knowledge transfer and intra-firm trade.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica 77*(3), 623–685.

Bloom, N., R. Sadun, and J. Van Reenen (2016). Management as a technology? Technical report, National Bureau of Economic Research.

Blundell, R. and S. Bond (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics 87*(1), 115 – 143.

Blundell, R. and S. Bond (2000). Gmm estimation with persistent panel data: an application to production functions. *Econometric Reviews 19*(3), 321–340.

Bond, S. and M. Söderbom (2005). Adjustment costs and the identification of cobb douglas production functions. Technical report, IFS Working Papers, Institute for Fiscal Studies (IFS).

Bond, S. and J. Van Reenen (2007). Chapter 65 microeconometric models of investment and employment. Volume 6, Part A of *Handbook of Econometrics*, pp. 4417 – 4498. Elsevier.

Branstetter, L. G., R. Fisman, and C. F. Foley (2006). Do stronger intellectual property rights increase international technology transfer? empirical evidence from u. s. firm-level panel data*. *The Quarterly Journal of Economics 121*(1), 321.

Bruno, M. (1978). Duality, intermediate inputs and value-added. *2*.

Bureau van Dijk Electronic Publishing (2011). Amadeus database. `http://www.bvdinfo.com/en-us/our-products/company-information/international/amadeus`.

Caballero, R. J. (1999). Aggregate investment. *Handbook of macroeconomics 1*, 813–862.

Caballero, R. J., K. N. Cowan, E. M. Engel, and A. Micco (2013). Effective labor regulation and microeconomic flexibility. *Journal of Development Economics 101*, 92 – 104.

Caballero, R. J. and E. M. R. A. Engel (1993). Microeconomic adjustment hazards and aggregate dynamics. *The Quarterly Journal of Economics 108*(2), 359–383.

Caballero, R. J. and E. M. R. A. Engel (1999). Explaining investment dynamics in u.s. manufacturing: A generalized (s, s) approach. *Econometrica 67*(4), 783–826.

Caballero, R. J., E. M. R. A. Engel, J. C. Haltiwanger, M. Woodford, and R. E. Hall (1995). Plant-level adjustment and aggregate investment dynamics. *Brookings Papers on Economic Activity 1995*(2), 1–54.

Caballero, R. J., E. M. R. A. Engel, and H. John (1997). Aggregate employment dynamics: Building from microeconomic evidence. *The American Economic Review 87*(1), 115–137.

Caballero, R. J. and J. V. Leahy (1996). Fixed costs: The demise of marginal q.

Card, D., J. Heining, and P. Kline (2013). Workplace heterogeneity and the rise of west german wage inequality. *The Quarterly Journal of Economics*.

Clerides, S. K., S. Lach, and J. R. Tybout (1998). Is learning by exporting important? micro-dynamic evidence from colombia, mexico, and morocco. *The Quarterly Journal of Economics 113*(3), 903–947.

Coe, D. T. and E. Helpman (1995). International r&d spillovers. *European Economic Review 39*(5), 859 – 887.

Collard-Wexler, A. and J. De Loecker (2015, January). Reallocation and technology: Evidence from the us steel industry. *American Economic Review 105*(1), 131–71.

Connolly, M. (2003). The dual nature of trade: measuring its impact on imitation and growth. *Journal of Development Economics 72*(1), 31 – 55.

Contreras, J. (2008). An empirical model of factor adjustment dynamics.

Cooper, R. and J. Haltiwanger (1993). The aggregate implications of machine replacement: Theory and evidence. *The American Economic Review 83*(3), 360–382.

Cooper, R., J. Haltiwanger, and L. Power (1999, September). Machine replacement and the business cycle: Lumps and bumps. *American Economic Review 89*(4), 921–946.

Cooper, R., J. Haltiwanger, and J. L. Willis (2007). Search frictions: Matching aggregate and establishment observations. *Journal of Monetary Economics 54, Supplement*, 56 – 78. Supplement issue: October 20-21 2006 Research Conference on 'Microeconomic

Adjustment and Macroeconomic Dynamics' Sponsored by the Swiss National Bank (http://www.snb.ch) and Study Center Gerzensee (www.szgerzensee.ch).

Cooper, R., J. Haltiwanger, and J. L. Willis (2015). Dynamics of labor demand: Evidence from plant-level observations and aggregate implications. *Research in Economics 69*(1), 37 – 50.

Cooper, R. and J. L. Willis (2004). A comment on the economics of labor adjustment: Mind the gap: Rejoinder. *The American Economic Review 94*(4), 1245–1247.

Cooper, R. and J. L. Willis (2009). The cost of labor adjustment: Inferences from the gap. *Review of Economic Dynamics 12*(4), 632 – 647.

Cooper, R. W. and J. C. Haltiwanger (2006). On the nature of capital adjustment costs. *The Review of Economic Studies 73*(3), 611–633.

Coşar, A. K., N. Guner, and J. Tybout (2016, March). Firm dynamics, job turnover, and wage distributions in an open economy. *American Economic Review 106*(3), 625–63.

Costinot, A., J. Vogel, and S. Wang (2013). An elementary theory of global supply chains. *The Review of Economic Studies 80*(1), 109–144.

Crinò, R. (2009). Offshoring, multinationals and labor market: A review of the empirical literature. *Journal of Economic Surveys 23*(2), 197–249.

Davis, S. J. and J. Haltiwanger (1992). Gross job creation, gross job destruction, and employment reallocation. *The Quarterly Journal of Economics 107*(3), 819–863.

Davis, S. J., J. C. Haltiwanger, and S. Schuh (1998). Job creation and destruction. *MIT Press Books 1*.

De Loecker, J. (2007). Do exports generate higher productivity? evidence from slovenia. *Journal of International Economics 73*(1), 69 – 98.

De Loecker, J. (2011). Product differentiation, multiproduct firms, and estimating the impact of trade liberalization on productivity. *Econometrica 79*(5), 1407–1451.

De Loecker, J. (2013, August). Detecting learning by exporting. *American Economic Journal: Microeconomics 5*(3), 1–21.

De Loecker, J. and P. K. Goldberg (2014). Firm performance in a global market. *Annual Review of Economics 6*(1), 201–227.

De Loecker, J., P. K. Goldberg, A. K. Khandelwal, and N. Pavcnik (2016). Prices, markups, and trade reform. *Econometrica 84*(2), 445–510.

De Loecker, J. and F. Warzynski (2012, May). Markups and firm-level export status. *American Economic Review 102*(6), 2437–71.

Dietzenbacher, E., B. Los, R. Stehrer, M. Timmer, and G. de Vries (2013). The construction of world input-output tables in the wiod project. *Economic Systems Research 25*(1), 71–98.

Diewert, W. E. (1978). Duality approaches to microeconomic theory.

Dixit, A. (1992). Investment and hysteresis. *The Journal of Economic Perspectives 6*(1), 107–132.

Dixit, A. K. and R. S. Pindyck (1994). *Investment under uncertainty.* Princeton university press.

Dobbelaere, S. and M. Vancauteren (2014). Market imperfections, skills and total factor productivity: Firm-level evidence on belgium and the netherlands. *NBB Working Paper Series* (267).

Doms, M. and T. Dunne (1998). Capital adjustment patterns in manufacturing plants. *Review of Economic Dynamics 1*(2), 409 – 429.

Doraszelski, U. and J. Jaumandreu (2013). R&d and productivity: Estimating endogenous productivity. *The Review of Economic Studies*.

Doraszelski, U. and J. Jaumandreu (2014). Measuring the bias of technological change.

Dumont, M., G. Rayp, M. Verschelde, and B. Merlevede (2016). The contribution of start-ups and young firms to industry-level efficiency growth. *Applied Economics 48*(59), 5786–5801.

Dustmann, C., J. Ludsteck, and U. Schönberg (2009). Revisiting the german wage structure. *The Quarterly Journal of Economics 124*(2), 843–881.

Edmond, C., V. Midrigan, and D. Y. Xu (2015, October). Competition, markups, and the gains from international trade. *American Economic Review 105*(10), 3183–3221.

Egger, H. and U. Kreickemeier (2009). Firm heterogeneity and the labor market effects of trade liberalization*. *International Economic Review 50*(1), 187–216.

Epifani, P. and G. Gancia (2006). Increasing returns, imperfect competition, and factor prices. *The Review of Economics and Statistics 88*(4), 583–598.

Epifani, P. and G. Gancia (2011). Trade, markup heterogeneity and misallocations. *Journal of International Economics 83*(1), 1 – 13.

Epifani, P. and G. A. Gancia (2009, March). Trade, markup heterogeneity and misallocations. CEPR Discussion Papers 7217, C.E.P.R. Discussion Papers.

Eslava, M., J. Haltiwanger, A. Kugler, and M. Kugler (2010). Factor adjustments after deregulation: panel evidence from colombian plants. *The Review of Economics and Statistics 92*(2), 378–391.

Eslava, M., J. Haltiwanger, A. Kugler, and M. Kugler (2013). Trade and market selection: Evidence from manufacturing plants in colombia. *Review of Economic Dynamics 16*(1), 135 – 158. Special issue: Misallocation and Productivity.

European Commission (2017). What is an sme? `http://ec.europa.eu/growth/smes/business-friendly-environment/sme-definition_en`.

Fajgelbaum, P. D. (2013). Labor market frictions, firm growth, and international trade.

Fally, T. (2011). On the fragmentation of production in the us. *University of Colorado-Boulder*.

Feenstra, R. C. (2003). A homothetic utility function for monopolistic competition models, without constant price elasticity. *Economics Letters 78*(1), 79 – 86.

Feenstra, R. C. and G. H. Hanson (1996). Globalization, outsourcing, and wage inequality. *The American Economic Review 86*(2), 240–245.

Feenstra, R. C. and G. H. Hanson (1999). The impact of outsourcing and high-technology capital on wages: Estimates for the united states, 1979–1990. *The Quarterly Journal of Economics 114*(3), 907–940.

Felbermayr, G., J. Prat, and H.-J. Schmerer (2011). Globalization and labor market outcomes: Wage bargaining, search frictions, and firm heterogeneity. *Journal of Economic Theory 146*(1), 39 – 73.

Felbermayr, G. J., G. Impullitti, and J. Prat (2014). Firm dynamics and residual inequality in open economies.

Fernandes, A. M. (2007). Trade policy, trade volumes and plant-level productivity in colombian manufacturing industries. *Journal of International Economics 71*(1), 52 – 71.

Fernandes, A. M. and A. E. Isgut (2015). Learning-by-exporting effects: Are they for real? *Emerging Markets Finance and Trade 51*(1), 65–89.

Foster, L., J. Haltiwanger, and C. J. Krizan (2002). The link between aggregate and micro productivity growth: Evidence from retail trade. Technical report, National Bureau of Economic Research.

Foster, L., J. Haltiwanger, and C. J. Krizan (2006). Market selection, reallocation, and restructuring in the us retail trade sector in the 1990s. *The Review of Economics and Statistics 88*(4), 748–758.

Foster, L., J. Haltiwanger, and C. Syverson (2008, March). Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review 98*(1), 394–425.

Foster, L., J. C. Haltiwanger, and C. J. Krizan (2001). Aggregate productivity growth. lessons from microeconomic evidence. In *New developments in productivity analysis*, pp. 303–372. University of Chicago Press.

Fox, J. T. and V. Smeets (2011). Does input quality drive measured differences in firm productivity? *International Economic Review 52*(4), 961–989.

Freeman, R. B. (2010). Globalization of scientific and engineering talent: international mobility of students, workers, and ideas and the world economy. *Economics of Innovation and New Technology 19*(5), 393–406.

Frey, B. S. and R. Jegen (2001). Motivation crowding theory. *Journal of Economic Surveys 15*(5), 589–611.

Frey, B. S., F. Oberholzer-Gee, and R. Eichenberger (1996). The old lady visits your backyard: A tale of morals and markets. *Journal of Political Economy 104*(6), 1297–1313.

Galeotti, M. and F. Schiantarelli (1991). Generalized q models for investment. *The Review of Economics and Statistics 73*(3), 383–392.

Gali, J., M. Gertler, and J. D. Lopez-Salido (2007). Markups, gaps, and the welfare costs of business fluctuations. *The Review of Economics and Statistics 89*(1), 44–59.

Gandhi, A., S. Navarro, and D. Rivers (2016). On the identification of production functions: How heterogeneous is productivity?

Garcia-Macia, D., C.-T. Hsieh, and P. J. Klenow (2016, December). How destructive is innovation? Working Paper 22953, National Bureau of Economic Research.

Garcia-Marin, A. and N. Voigtländer (2013, May). Exporting and plant-level efficiency gains: It's in the measure. Working Paper 19033, National Bureau of Economic Research.

Gestrin, M. (2016). Trends in foreign direct investment and their implications for development. *Development Co-operation Report*, 49–66.

Ginarte, J. C. and W. G. Park (1997). Determinants of patent rights: A cross-national study. *Research policy 26*(3), 283–301.

Goldberger, A. S. (1968). The interpretation and estimation of cobb-douglas functions. *Econometrica 36*(3/4), 464–472.

Görg, H., A. Hanley, and E. Strobl (2008). Productivity effects of international outsourcing: Evidence from plant-level data. *The Canadian Journal of Economics / Revue canadienne d'Economique 41*(2), 670–688.

Griliches, Z. (1998). R&d and productivity: The unfinished business. In *R&D and Productivity: The Econometric Evidence*, pp. 269–283. University of Chicago Press.

Griliches, Z. and J. Mairesse (1999). Production functions: The search for identification. pp. 169–203. Cambridge Books Online.

Grossman, G. M. and E. Helpman (1991). Quality ladders in the theory of growth. *The Review of Economic Studies 58*(1), 43–61.

Grossman, G. M. and E. Helpman (1995). Chapter 25 technology and trade. Volume 3 of *Handbook of International Economics*, pp. 1279 – 1337. Elsevier.

Grossman, G. M. and E. Helpman (2002). Integration versus outsourcing in industry equilibrium. *The Quarterly Journal of Economics 117*(1), 85–120.

Grossman, G. M. and E. Helpman (2005). Outsourcing in a global economy. *The Review of Economic Studies 72*(1), 135–159.

Guadalupe, M., O. Kuzmina, and C. Thomas (2012). Innovation and foreign ownership. *The American Economic Review 102*(7), 3594–3627.

Gumpert, A. (2015). The Organization of Knowledge in Multinational Firms. CESifo Working Paper Series 5401, CESifo Group Munich.

Hall, R. E. (2004). Measuring factor adjustment costs. *The Quarterly Journal of Economics 119*(3), 899–927.

Hall, R. E. and D. W. Jorgenson (1969). Tax policy and investment behavior: Reply and further results. *The American Economic Review 59*(3), 388–401.

Halpern, L., M. Koren, and A. Szeidl (2015, December). Imported inputs and productivity. *American Economic Review 105*(12), 3660–3703.

Hamermesh, D. S. (1989). Labor demand and the structure of adjustment costs. *The American Economic Review 79*(4), 674–689.

Hamermesh, D. S. (1996). *Labor Demand*. Princeton University Press.

Hamermesh, D. S. and G. A. Pfann (1996). Adjustment costs in factor demand. *Journal of Economic Literature 34*(3), 1264–1292.

Hausman, J. (2001). Mismeasured variables in econometric analysis: Problems from the right and problems from the left. *The Journal of Economic Perspectives 15*(4), 57–67.

Helpman, E. and O. Itskhoki (2010). Labour market rigidities, trade and unemployment. *The Review of Economic Studies 77*(3), 1100–1137.

Helpman, E., O. Itskhoki, M.-A. Muendler, and S. J. Redding (2016). Trade and inequality: From theory to estimation. *Review of Economic Studies*.

Helpman, E., O. Itskhoki, and S. Redding (2010a). Inequality and unemployment in a global economy. *Econometrica 78*(4), 1239–1283.

Helpman, E., O. Itskhoki, and S. Redding (2010b). Unequal effects of trade on workers with different abilities. *Journal of the European Economic Association 8*(2-3), 421–433.

Helpman, E., O. Itskhoki, and S. Redding (2011). Trade and labor market outcomes. Technical report, National Bureau of Economic Research.

Helpman, E., M. J. Melitz, and S. R. Yeaple (2004, March). Export versus fdi with heterogeneous firms. *American Economic Review 94*(1), 300–316.

Hobijn, B. and A. Şahin (2013). Firms and flexibility. *Economic Inquiry 51*(1), 922–940.

Holt, C. C., F. Modigliani, J. F. Muth, and H. A. Simon (1960). Planning, production, inventories, and work force.

Hopenhayn, H. and R. Rogerson (1993). Job turnover and policy evaluation: A general equilibrium analysis. *Journal of Political Economy 101*(5), 915–938.

Hopenhayn, H. A. (2014). Firms, misallocation, and aggregate productivity: A review. *Annual Review of Economics 6*(1), 735–770.

Hulten, C. R. (2001). Total factor productivity: a short biography. In *New developments in productivity analysis*, pp. 1–54. University of Chicago Press.

Hulten, C. R. (2010). Chapter 23 - growth accounting. In B. H. Hall and N. Rosenberg (Eds.), *Handbook of the Economics of Innovation, Volume 2*, Volume 2 of *Handbook of the Economics of Innovation*, pp. 987 – 1031. North-Holland.

Hyytinen, A., P. Ilmakunnas, and M. Maliranta (2016). Olley–pakes productivity decomposition: computation and inference. *Journal of the Royal Statistical Society: Series A (Statistics in Society) 179*(3), 749–761.

Ito, K. and K. Tanaka (2012). Does material and service offshoring improve domestic productivity? evidence from japanese manufacturing industries. In *Quantitative Analysis Of Newly Evolving Patterns Of International Trade: Fragmentation, Offshoring of Activities, and Vertical Intra-Industry Trade*, pp. 49–99.

Javorcik, B. (2010). Foreign direct investment and international technology transfer. *Encyclopedia of Financial Globalization*.

Javorcik, B. S. (2004a). The composition of foreign direct investment and protection of intellectual property rights: Evidence from transition economies. *European Economic Review 48*(1), 39 – 62.

Javorcik, B. S. (2004b). Does foreign direct investment increase the productivity of domestic firms? in search of spillovers through backward linkages. *The American Economic Review 94*(3), 605–627.

Johnson, R. C. and G. Noguera (2012). Fragmentation and trade in value added over four decades.

Jovanovic, B. and Y. Nyarko (1996). Learning by doing and the choice of technology. *Econometrica 64*(6), 1299–1310.

Kasahara, H. and B. Lapham (2013). Productivity and the decision to import and export: Theory and evidence. *Journal of International Economics 89*(2), 297 – 316.

Kasahara, H. and J. Rodrigue (2008). Does the use of imported intermediates increase productivity? plant-level evidence. *Journal of Development Economics 87*(1), 106 – 118.

Keller, W. and S. R. Yeaple (2013, June). The gravity of knowledge. *American Economic Review 103*(4), 1414–44.

Kellogg, R. (2011). Learning by drilling: Interfirm learning and relationship persistence in the texas oilpatch. *The Quarterly Journal of Economics 126*(4), 1961–2004.

Klette, T. J. and Z. Griliches (1996). The inconsistency of common scale estimators when output prices are unobserved and endogenous. *Journal of Applied Econometrics 11*(4), 343–361.

Koeniger, W. and J. Prat (2007). Employment protection, product market regulation and firm selection. *The Economic Journal 117*(521), F302–F332.

Konings, J. and S. Vanormelingen (2015). The impact of training on productivity and wages: firm-level evidence. *Review of Economics and Statistics 97*(2), 485–497.

Kramarz, F. and M.-L. Michaud (2010). The shape of hiring and separation costs in france. *Labour Economics 17*(1), 27 – 37.

Kubon-Gilke, G. (1998). Not just for the money. an economic theory of personal motivation.

Kugler, M. and E. Verhoogen (2012). Prices, plant size, and product quality. *The Review of Economic Studies 79*(1), 307–339.

Lagos, R. (2006). A model of tfp. *The Review of Economic Studies 73*(4), 983–1007.

Lapatinas, A. (2012). On the interrelation of capital and labor adjustment costs at the firm level. *Studies in Nonlinear Dynamics & Econometrics 16*(3).

Letterie, W. A. and G. A. Pfann (2007). Structural identification of high and low investment regimes. *Journal of Monetary Economics 54*(3), 797 – 819.

Letterie, W. A., G. A. Pfann, and J. Polder (2004). Factor adjustment spikes and interrelation: an empirical investigation. *Economics Letters 85*(2), 145 – 150.

Levinsohn, J. and A. Petrin (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies 70*(2), 317–341.

Lileeva, A. and D. Trefler (2010). Improved access to foreign markets raises plant-level productivity…for some plants. *The Quarterly Journal of Economics 125*(3), 1051–1099.

Liu, R. and D. Trefler (2008). Much ado about nothing: American jobs and the rise of service outsourcing to china and india. Technical report, National Bureau of Economic Research.

Lucas, R. E. and E. C. Prescott (1971). Investment under uncertainty. *Econometrica 39*(5), 659–681.

Maliranta, M. and N. Määttänen (2015). An augmented static olley–pakes productivity decomposition with entry and exit: Measurement and interpretation. *Economica 82*, 1372–1416.

Manjón, M., J. A. Máñez, M. E. Rochina-Barrachina, and J. A. Sanchis-Llopis (2013). Reconsidering learning by exporting. *Review of World Economics 149*(1), 5–22.

Markusen, J. R. (1989). Trade in producer services and in other specialized intermediate inputs. *The American Economic Review 79*(1), 85–95.

Marschak, J. and W. H. Andrews (1944). Random simultaneous equations and the theory of production. *Econometrica 12*(3/4), 143–205.

Mayer, T., M. J. Melitz, and G. I. P. Ottaviano (2014, February). Market size, competition, and the product mix of exporters. *American Economic Review 104*(2), 495–536.

Mayer, T. and G. I. P. Ottaviano (2008). The happy few: The internationalisation of european firms. *Intereconomics 43*(3), 135–148.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica 71*(6), 1695–1725.

Melitz, M. J. and G. I. P. Ottaviano (2008). Market size, trade, and productivity. *The Review of Economic Studies 75*(1), 295.

Melitz, M. J. and S. Polanec (2015). Dynamic olley-pakes productivity decomposition with entry and exit. *The RAND Journal of Economics 46*(2), 362–375.

Melitz, M. J. and S. J. Redding (2014). *Heterogeneous Firms and Trade*, Volume 4, pp. 1–54. Elsevier.

Mendershausen, H. (1938). On the significance of professor douglas' production function. *Econometrica 6*(2), 143–153.

Merlevede, B., M. de Zwaan, K. Lenaerts, and V. Purice (2015). Multinational networks, domestic,and foreign firms in europe.

Merlevede, B. and B. Michel (2013). Downstream offshoring and firm-level employment: Evidence for belgian manufacturing firms. *Federal Planning Bureau Working Paper 16-13*, 308–347.

Merz, M. and E. Yashiv (2007). Labor and the market value of the firm. *The American Economic Review 97*(4), 1419–1431.

Michel, B. and F. Rycx (2014). Productivity gains and spillovers from offshoring. *Review of International Economics 22*(1), 73–85.

Moran, T. H. (2007). How to investigate the impact of foreign direct investment on development and use the results to guide policy. In *Brookings Trade Forum*, Volume 2007, pp. 1–60. Brookings Institution Press.

Nickell, S. (1974). On the role of expectations in the pure theory of investment. *The Review of Economic Studies 41*(1), 1–19.

Nilsen, Ø. A., A. Raknerud, M. Rybalka, and T. Skjerpen (2009). Lumpy investments, factor adjustments, and labour productivity. *Oxford Economic Papers 61*(1), 104–127.

Nilsen, Ø. A., K. G. Salvanes, and F. Schiantarelli (2007). Employment changes, the structure of adjustment costs, and plant size. *European Economic Review 51*(3), 577 – 598.

Nilsen, Ø. A. and F. Schiantarelli (2003). Zeros and lumps in investment: Empirical evidence on irreversibilities and nonconvexities. *The Review of Economics and Statistics 85*(4), 1021–1037.

OECD (Accessed on 22 March 2017). Dataset: Business enterprise r-d expenditure by size class and by source of funds. `https://stats.oecd.org/Index.aspx?DataSetCode=BERD_SIZE`.

Olley, G. S. and A. Pakes (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica 64*(6), 1263–1297.

Osterloh, M. and B. S. Frey (2000). Motivation, knowledge transfer, and organizational forms. *Organization Science 11*(5), 538–550.

Ouattara, B. and S. Standaert (2017). Inequality and property rights revisited. Technical report, Ghent University, Faculty of Economics and Business Administration.

Pakes, A. (1994). Dynamic structural models, problems and prospects: mixed continuous discrete controls and market interactions. In C. A. Sims (Ed.), *Advances in Econometrics*, Volume 2, pp. 171–274. Cambridge University Press. Cambridge Books Online.

Parente, S. L. (1994). Technology adoption, learning-by-doing, and economic growth. *Journal of Economic Theory 63*(2), 346 – 369.

Park, W. G. (2008). International patent protection: 1960–2005. *Research Policy 37*(4), 761 – 766.

Park, W. G. and D. Lippoldt (2005). International licensing and the strengthening of intellectual property rights in developing countries during the 1990s. *OECD Economic Studies 2005*(1), 7–48.

Pavcnik, N. (2002). Trade liberalization, exit, and productivity improvements: Evidence from chilean plants. *The Review of Economic Studies 69*(1), 245.

Peck, S. C. (1974). Alternative investment models for firms in the electric utilities industry. *The Bell Journal of Economics and Management Science 5*(2), 420–458.

Peters, M. (2013). Heterogeneous mark-ups, growth and endogenous misallocation.

Petrin, A. and J. Levinsohn (2012). Measuring aggregate productivity growth using plant-level data. *The RAND Journal of Economics 43*(4), 705–725.

Petrin, A. and J. Sivadasan (2006). Job security does affect economic efficiency: Theory, a new statistic, and evidence from chile.

Petrin, A. and J. Sivadasan (2013). Estimating lost output from allocative inefficiency, with an application to chile and firing costs. *Review of Economics and Statistics 95*(1), 286–301.

Pindyck, R. S. (1991). Irreversibility, uncertainty, and investment. *Journal of Economic Literature 29*(3), 1110–1148.

Ramondo, N., V. Rappoport, and K. J. Ruhl (2016). Intrafirm trade and vertical fragmentation in u.s. multinational corporations. *Journal of International Economics 98*, 51 – 59.

Rota, P. (2004). Estimating labor demand with fixed costs. *International Economic Review 45*(1), 25–48.

Rothschild, M. (1971). On the cost of adjustment. *The Quarterly Journal of Economics 85*(4), 605–622.

Rust, J. (1987). Optimal replacement of gmc bus engines: An empirical model of harold zurcher. *Econometrica 55*(5), 999–1033.

Sakellaris, P. (2004). Patterns of plant adjustment. *Journal of Monetary Economics 51*(2), 425 – 450.

Salop, S. C. (1979). Monopolistic competition with outside goods. *The Bell Journal of Economics 10*(1), 141–156.

Sampson, T. (2016). Dynamic selection: An idea flows theory of entry, trade, and growth. *The Quarterly Journal of Economics 131*(1), 315.

Servén, L. (1997). Irreversibility, uncertainty and private investment: Analytical issues and some lessons for africa. *Journal of African Economies 6*(3), 229–68.

Shapiro, M. D. (1986). The dynamic demand for capital and labor. *The Quarterly Journal of Economics 101*(3), 513–542.

Slaughter, M. J. (2004). *Insourcing Jobs: Making the global economy work for America.* OFII.

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics 39*(3), 312–320.

Stokey, N. L. (1988). Learning by doing and the introduction of new goods. *Journal of Political Economy 96*(4), 701–717.

Teece, D. J. (1982). Towards an economic theory of the multiproduct firm. *Journal of Economic Behavior & Organization 3*(1), 39 – 63.

Tobin, J. (1969). A general equilibrium approach to monetary theory. *Journal of Money, Credit and Banking 1*(1), 15–29.

Tomiura, E. (2007). Foreign outsourcing, exporting, and fdi: A productivity comparison at the firm level. *Journal of International Economics 72*(1), 113 – 127.

Topalova, P. and A. Khandelwal (2011). Trade liberalization and firm productivity: The case of india. *Review of economics and statistics 93*(3), 995–1009.

Van Beveren, I. and S. Vanormelingen (2014). Human capital, firm capabilities and productivity growth. *NBB Working Paper Series* (257).

Van Biesebroeck, J. (2005). Exporting raises productivity in sub-saharan african manufacturing firms. *Journal of International Economics 67*(2), 373 – 391.

Van Biesebroeck, J. (2008). The sensitivity of productivity estimates: Revisiting three important debates. *Journal of Business & Economic Statistics 26*(3), 311–328.

Vogel, A. and J. Wagner (2010). Higher productivity in importing german manufacturing firms: self-selection, learning from importing, or both? *Review of World Economics / Weltwirtschaftliches Archiv 145*(4), 641–665.

Yatchew, A. (1998). Nonparametric regression techniques in economics. *Journal of Economic Literature 36*(2), 669–721.

Nederlandse samenvatting

De continue afname in handels- en communicatiekosten van de laatste decennia hebben geresulteerd in een versterking van de onderlinge verbondenheid tussen economieën over de hele wereld. In dit proces, dat ook de globalisatie golf genoemd wordt, zijn bedrijven de voornaamste drijvers van economische groei dankzij hun cruciale rol in het produceren van goederen en diensten, het creëren van jobs, en het voortbrengen van handel en innovatie.

Voor beleidsmakers belast met het verhogen van de welvaart is het dan ook essentieel om te begrijpen hoe bedrijven werken en—in het bijzonder—hoe ze beslissingen maken. In een perfecte wereld zouden onderzoekers en beleidsmakers dit onderliggende proces voor elk bedrijf kunnen identificeren en de volledige productie structuur (of productietechnologie) in kaart kunnen brengen. Jammer genoeg is dit in de praktijk onmogelijk aangezien de input voor deze processen in vele gevallen niet waarneembaar is (bv. managementbeleid, de vakkundigheid van werknemers, innovatie, etc.) of moeilijk te meten is op een wetenschappelijke en objectieve manier (bv. de karakteristieken van werknemers, knowhow, etc.)

Gegeven deze informatiebeperkingen kunnen we de productietechnologie van een bedrijf slechts tot op zekere hoogte identificeren. De niet-identificeerbare restant word in de handelsliteratuur samengebracht onder de verzamel term 'productiviteit.' Naar analogie met de productietechnologie, heeft de productiviteit van bedrijven een bepaalde structuur en kan deze beïnvloed worden door verschillende factoren. Sommige van deze factoren liggen in de beslissingensfeer van het bedrijf (bv. beslissingen i.v.m. import, export of offshoring), terwijl andere bepaald worden door de omgeving van het bedrijf (bv. externe handelsschokken, veranderingen in de regulering, economische crisissen, etc.).

Tijdens de laatste globalisatiegolf is het niveau van complexiteit van de productietechnologie en productiviteitsstructuur nog verder verhoogd. Om de huidige structuur te ontrafelen is het daarom ook noodzakelijk geworden om inzicht te verwerven in de onderliggende processen op micro-economisch niveau. Aangezien productiviteit niet rechtstreeks geobserveerd kan worden, zijn we daarbij gedwongen om dit te berekenen of te schatten op een indirecte manier.

Deze elementen indachtig, kan ik de grootste bijdrage van mijn thesis in twee punten samenvatten. Ten eerste benadruk ik in deze thesis het belang van productiviteitsmetingen door aan te tonen hoe verschillende metingen, veronderstellingen en schattingsprocedures economische bevindingen beïnvloeden. Hiertoe focus ik op een aantal verkeerde specificaties die in de gangbare literatuur vaak buiten beschouwing gelaten worden bij het identificeren van productiviteit en de determinanten daarvan. Ten tweede probeer ik de determinanten van productiviteit ten gronde uit te diepen. Specifiek richt ik mij op handel, productieketens, markt imperfecties en eigendomsstructuren in een internationale en sterk verweven context. Deze bijdragen zijn beschreven in de vier hoofdstukken van mijn doctoraatsthesis, die hieronder kort worden beschreven.

Hoofdstuk 2 toont aan dat wanneer de productiviteit op een incorrecte wijze wordt geschat, dit tot foutieve conclusies kan leiden over de evolutie van de totale productiviteit en zijn verschillende componenten. Eens voor deze fouten wordt gecontroleerd, ontleden we de totale productiviteit in verschillende groepen die opgesteld zijn volgens, economische significantie. Onze resultaten wijzen er op dat de productiviteit van bedrijven is toegenomen overheen de tijd. Bovendien, zijn de bedrijven die de grootste toename hebben gekend zijn degenen die het meest geïnternationaliseerd en het grootst zijn. Bij andere bedrijven was het effect veel kleiner, waardoor de totale productiviteit zijn maximale potentieel niet kon bereiken.

Hoofdstuk 3 gaat na of er indirecte effecten zijn van internationalisering op de binnenlandse productieketen. Ten eerste tonen we aan dat wanneer de schattingen geen rekening houden met bekende specificatie problemen van de productietechnologie, dit leidt tot foute conclusies over de eigenlijke determinanten van productiviteit. Ten tweede vinden we dat wanneer bedrijven aankopen plaatsen bij andere exporterende bedrijven, zij ook hogere niveaus van productiviteit kennen. Dit is hoogstwaarschijnlijk gedreven door het feit dat ze toegang hebben tot intermediaire goederen van hogere kwaliteit die ook geëxporteerd worden.

Hoofdstuk 4 bestudeert hoe veranderingen in de omgeving van het bedrijf gekoppeld met de toename in internationale handel de productiviteit beïnvloeden. Enerzijds vinden we dat wanneer lokale bedrijven op de arbeidsmarkt meer frictie ondervinden, hun productiviteit daarna in grotere mate toeneemt dan bij exporterende bedrijven. Dit suggereert dat bedrijven die enkel voor de lokale markt produceren minder bereid zijn om kosten van veranderingen in hun werknemersbestand te dragen. Bijgevolg vallen ze vaker terug op aanpassingen in de bedrijfsorganisatie en management praktijken, wat zich op termijn vertaalt in een verhoogde productiviteit door middel van leereffecten. De productiviteitseffecten van fricties in de kapitaalmarkt zijn anderzijds minder frequent en beïnvloeden alle types bedrijven op dezelfde manier, wat er op wijst dat kapitaal minder flexibel is en duurder is om aan te passen.

Hoofdstuk 5, ten slotte, bekijkt hoe de structuur van eigenaarschap de productietechnologie en productiviteit beïnvloedt. Samen met mijn coauteur, kwantificeer ik het belang van technologie transfers van verscheidene eigenschapsstructuren. Hierbij, bevestigen we de theorie dat bedrijfsgrenzen er bestaan om de transfers van immateriële goederente faciliteren.

Samengevat, verwacht ik dat dit doctoraatsonderzoek ons begrip versterkt over welk type bedrijf het meeste bijdraagt aan economische groei of achteruitgang, tijdens positieve en negatieve economische tijden. Daarbij hoop ik beleidsmakers en instituties een sterker referentiepunt te kunnen bieden om toekomstig beleid te vormen.